Confidential

UNITED STATES DISTRICT COURT

WESTERN DISTRICT OF NEW YORK

IN RE: ROCK ‘N PLAY SLEEPER MARKETING, SALES PRACTICES, AND PRODUCTS LIABILITY LITIGATION

Case No.: 1:19-md-02903-GWC

EXPERT REBUTTAL REPORT OF OLIVIER TOUBIA, PH.D.

June 16, 2021

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I. QUALIFICATIONS

1. My name is Olivier Toubia. I am the Glaubinger Professor of Business at Columbia Business School. The principal focus of my research has been in the areas of marketing research and various aspects of innovation, including idea generation and preference measurement. I teach core marketing courses and electives on innovation in the MBA and Executive MBA programs at Columbia Business School.

2. I currently serve as the chair of Columbia Business School Marketing Division. I am a member of Columbia University's Tenure Review Advisory Committee, which advises the Provost on tenure cases from the entire university.

3. I am the author or co-author of more than two dozen book chapters, articles, and papers. Approximately half of my publications have focused on preference measurement. The other half have focused on various topics including idea generation, social networks, and behavioral economics. I have developed market research techniques that enable marketing researchers, experts, and managers to measure consumers' preferences for attributes of both existing and hypothetical products. These methods have been employed numerous times by academic researchers, as well as practitioners from major international corporations.

4. I am the recipient of four John Little awards for best marketing paper published in *Marketing Science* or *Management Science*, the Paul Green award for best paper published in the *Journal of Marketing Research*, the ISMS (INFORMS Society for Marketing Science) Long Term Impact Award, the Don Lehmann award for best dissertation-based paper published in the *Journal of Marketing Research*, the John A. Howard best dissertation award, and the Frank M.

Bass outstanding dissertation award. I serve as Senior Editor for *Marketing Science*, one of the premier marketing academic journals. I authored the chapter on conjoint analysis in the 2018 Handbook of Marketing Analytics. In 2014, I co-authored a variety of teaching materials on conjoint analysis for Harvard Business School, including an online tutorial on conjoint analysis as well as guidelines for designing, conducting and analyzing a conjoint analysis survey.[1]

5. I frequently review academic research that involves surveys and preference measurement. Most of my work outside of Columbia University has involved surveys and other market research to measure consumers' attitudes and beliefs. My professional qualifications are described further in my curriculum vita, which is attached as **Appendix A**.

6. I have previously served as an expert witness in consumer class actions and patent infringement matters. I have evaluated issues relating to consumers' perceptions of, or preferences for, specific product attributes or features and opined on methods of calculating damages on a class-wide basis. I testified as an expert witness on these and other issues. A list of my testimony in the past four years is attached as **Appendix B**.

7. I am being compensated at my regular hourly rate of $750. I am being assisted in this matter by staff from Analysis Group, who are working at my direction. I receive compensation based on Analysis Group's staff billings in this matter. No compensation is contingent upon the content of my opinion or the outcome of this or any other matter.

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[1] *See* Elie Ofek and Olivier Toubia, "Conjoint Analysis: Online Tutorial," *Harvard Business School Tutorial*, April 2014 and Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014.

II. ASSIGNMENT AND BACKGROUND

A. Scope of Assignment

8. I have been asked by Manatt, Phelps & Phillips, counsel for Defendants, to provide expert analysis and testimony in this matter. Plaintiffs' proposed damages expert, Colin B. Weir, submitted a declaration in this matter dated February 8, 2021 (the "Weir Declaration"). I was asked to review, evaluate, and, where appropriate, respond to the portion of Mr. Weir's declaration and opinions that relate to his discussion regarding a proposed conjoint survey, as contained in Exhibit 3 to his declaration, which he calls "Conjoint Analysis."[2] In Exhibit 3, Mr. Weir purports to offer an opinion of how he might attempt to prepare a "conjoint survey" at some later point in this litigation.[3]

9. Mr. Weir's declaration states that he was "asked by Counsel to ascertain whether it is possible to determine damages on a class-wide basis using common evidence, and if so, to provide a framework for the calculation of the damages attributable to Plaintiffs' theory of liability in this case."[4] Mr. Weir does not opine on the merits of the case and appears to assume

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[2] Declaration of Colin B. Weir, February 8, 2021 ("Weir Declaration"), Exhibit 3.

[3] Mr. Weir's declaration describes how he would go about preparing a conjoint survey ("proposed survey") in a cursory fashion. An expert can provide the exact details of their proposed conjoint survey even if it has not been run yet. For example, in *McMorrow v. Mondelez*, a case in which Mr. Weir was an expert for plaintiffs, a different expert for plaintiffs, Dr. Michael Dennis, submitted: the cognitive interview questionnaire he used to conduct his background research; the full script for his screening and conjoint survey, including the exact attributes and levels he would use; and screenshots of online searches used to support his selection of attributes and levels. *See* Declaration of J. Michael Dennis, *McMorrow, et al. v. Mondelez International, Inc.*, 3:17-cv-02327-BAS-JLB, U.S. District Court for the Southern District of California, May 4, 2020, Attachments B-E. *See also,* Deposition of Colin B. Weir, March 11, 2021 ("Weir Deposition"), 298:25-299:14. However, as I explain below in Section VII, Mr. Weir's declaration and testimony do not provide crucial information about his proposed survey, including the selection of attributes and levels, sample selection, and planned pretest. As a result, it is not possible to determine whether these aspects of Mr. Weir's proposed survey would be reliable. Despite these omissions, I refer to Mr. Weir's "proposed survey," even though what Mr. Weir has provided is not close to being a survey that could be fielded without significant additional research and development.

[4] Weir Declaration, ¶ 5.

liability when outlining his theories of damages. Mr. Weir sets forth two theories of economic damages in his declaration: (1) full refund damages, and (2) diminution in value damages based on the "price difference due to the alleged safety risks."[5] Mr. Weir states that to "calculate such diminished value," he proposes "the use of conjoint analysis" through a survey.[6]

10. I have not been asked to evaluate and have no opinion about whether the safety issues that Plaintiffs allege in fact exist, or what they consist of, if they do exist. I have no opinion regarding Defendants' potential liability in this matter. However, for the purposes of my assignment, I assume liability on the part of the Defendants for the alleged false advertising in this matter. In addition, I have not been asked to directly respond to the damages opinions and proposed damages calculations offered in the Weir Declaration. My opinions relate to Mr. Weir's damages opinions to the extent that Mr. Weir opines on the basis of his proposed survey that diminution in value damages can be measured on a class-wide basis.

11. In formulating my opinions, I have relied upon the materials cited in this report and accompanying exhibits or appendices, or listed in **Appendix C**.[7]

B. Plaintiffs' Allegations

12. Plaintiffs allege that the Fisher-Price Rock 'n Play Sleeper ("Rock 'n Play Sleeper"), a rocking infant product, was falsely marketed as being safe for infant sleep, including for

[5] Weir Declaration, ¶¶ 14-17, 25-29. I address only the second of these two theories of economic damages set forth by Mr. Weir.

[6] Weir Declaration, Exhibit 3, ¶ 1.

[7] Unless materials have been inadvertently omitted, all materials that are cited in this report and accompanying exhibits or appendices are included in **Appendix C**.

overnight and prolonged sleep. Specifically, in their Consolidated Amended Complaint ("Complaint"), Plaintiffs allege that:

> As set forth below, inclined sleepers, including the Rock 'n Play Sleeper, are unsuitable for infant sleep and, in fact, are dangerous.[8]
>
> Defendants' marketing of this product as safe for infant sleep, including prolonged and overnight sleep, was intentional and overt. … This marketing was dangerously false and misleading, as the product is not safe for sleep, including prolonged or overnight sleep.[9]
>
> The Rock 'n Play Sleeper is inherently unsafe as a sleeper and unfit for its intended use. It poses a number of serious safety risks that led to many documented infant deaths and injuries.[10]
>
> Defendants' false and misleading marketing of this dangerous product, and knowing failure to disclose the grave risks of its use as a sleeper, including for overnight or prolonged sleep, allowed Defendants to reap vast profits at the expense of consumers who erroneously believed they were giving their babies a safe place to sleep.[11]
>
> Defendants' deceptive marketing of the product as a "Sleeper" that is safe for infant sleep, including overnight or prolonged sleep, is material to consumers' decision to purchase and/or own the product, because it causes consumers to reasonably believe the product is safe. Defendants should not have marketed the product as a "Sleeper" suitable for infant sleep, including prolonged or overnight sleep. Alternatively, Defendants should have disclosed in their marketing statements that using the product for sleep, including prolonged or overnight sleep, is dangerous and contrary to medical guidelines and recommendations because this information would be material to a consumer's decision as to whether to purchase and/or own the product.[12]

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[8] Consolidated Amended Complaint, *In Re: Rock 'n Play Sleeper Marketing, Sales Practices, and Products Liability Litigation*, 1:19-md-2903, October 28, 2019 ("Complaint"), ¶ 1.

[9] Complaint, ¶ 2.

[10] Complaint, ¶ 3.

[11] Complaint, ¶ 22.

[12] Complaint, ¶ 190.

13. Plaintiffs' Motion for Class Certification in this matter contains similar allegations:

> Between October 1, 2009, when the Fisher-Price Rock 'n Play Sleeper … was introduced to the market, and April 12, 2019, when … Defendants were forced to recall it … Defendants consistently marketed their Sleeper across all media using a single, overarching marketing message – that the Sleeper was fit for infant sleep, including overnight and prolonged sleep.[13]
>
> …this persistent and uniform marketing message portraying the Fisher-Price Rock 'n Play Sleeper as safe for infant sleep … was dangerously false, misleading, deceptive and unfair. [14]
>
> Defendants' marketing statements … were all designed to convey one consistent message to consumers – that the RNPS was a safe product, and that it was safe for infant sleep, including overnight sleep. Every RNPS marketed and sold by Defendants in the United States contained language that communicated safe, prolonged infant sleep as the intended use of the product directly on the package.[15]
>
> Defendants knew that parents to newborns were desperate for their children to sleep longer stretches, and they capitalized on this knowledge by emphasizing in their marketing that the RNPS was designed, and ideal, for infant sleep, including overnight sleep and naps.[16]
>
> While touting itself as a brand for safe sleep solutions, Fisher-Price never informed consumers, including Plaintiffs, that the RNPS was unsafe for overnight sleep. … Thus, consumers reasonably believed the Sleeper was safe for overnight sleep as advertised and that their infant could sleep safely in the product.[17]
>
> Defendants knowingly concealed and misrepresented safety concerns and dangers of the RNPS from consumers.[18]

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[13] Memorandum of Law in Support of Plaintiffs' Motion for Class Certification, *In Re: Fisher-Price Rock 'n Play Sleeper Marketing, Sales Practices, and Products Liability Litigation*, 1:19-md-2903, February 8, 2021 ("Motion for Class Certification"), p. 1.

Plaintiffs use the terms "Sleeper" and "RNPS" to mean the Rock 'n Play Sleeper.

[14] Motion for Class Certification, p. 2.

[15] Motion for Class Certification, p. 7.

[16] Motion for Class Certification, p. 9.

[17] Motion for Class Certification, p. 12.

[18] Motion for Class Certification, p. 13.

> … Defendants continued to utilize their Marketing Statements to convey the false message that the RNPS was safe for infant sleep.[19]

14. My understanding of Plaintiffs' allegations is also consistent with Mr. Weir's discussion of Plaintiffs' allegations in his declaration:

> I have been advised by Counsel for Plaintiffs that individuals purchased certain Fisher-Price Rock 'n Play Sleepers (the "Products") that were marketed as safe for infant sleep, including prolonged and overnight sleep. I have been further advised that Plaintiffs allege inclined sleepers, including the Rock 'n Play Sleeper, are unsuitable for infant sleep and, in fact, are unsafe for infant sleep. [20]
>
> Plaintiffs allege that the "Rock 'n Play Sleeper is inherently unsafe as a sleeper and unfit for its intended use. It poses a number of serious safety risks that led to many documented infant deaths and injuries."[21]

C. Parties

15. According to the Complaint, the named plaintiffs in this case ("Plaintiffs") include Elizabeth Alfaro, Emily Barton, Linda Black, Luke Cuddy, Rebecca Drover, Megan Fieker, Karen Flores, Nancy Hanson, Jena Huey, Samantha Jacoby, Megan Kaden, Kerry Mandley, Cassandra Mulvey, Joshua Nadel, Melanie Nilius Nowlin, Daniel Pasternacki, Jessie Poppe, Katharine Shaffer, Emily Simmonds, Josie Willis, and Renee Wray.[22]

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[19] Motion for Class Certification, p. 13.

[20] Weir Declaration, ¶ 5 (internal citations omitted).

[21] Weir Declaration, ¶ 9.

See also remarks by Plaintiffs' counsel: Transcript of Status Conference, *In re: Rock 'n Play Sleeper Marketing, Sales Practices, and Products Liability Litigation*, Case No. 1:19-md-2903, 16:23–17:2 ("the whole underlying theory of our case is that this product is unsafe for infant sleep") and 21:18–21 ("This about a product that is unsafe for infant sleep… when used as instructed with the restraints.").

[22] Complaint, ¶¶ 24-46.

16. The defendants in this matter ("Defendants") are Fisher-Price, Inc., a Delaware corporation with its principal place of business in East Aurora, Erie County, New York, and its corporate parent Mattel, Inc.[23] Fisher-Price, Inc. designs, manufactures, distributes, markets, advertises, labels, and sells products for the care of infants and preschool children.[24] The product at issue in this case is the Rock 'n Play Sleeper.[25]

D. Putative Classes

17. Plaintiffs define multiple putative classes in this matter. Plaintiffs seek damages for 12 proposed statewide classes, which consist of purchasers of the products in each of those 12 states:

> All persons, other than Mattel, Inc. and Fisher-Price, Inc., and their employees, who purchased any model of Fisher-Price Rock 'n Play Sleeper in [each state set forth herein] from October 1, 2009 until the date of notice. These states are as follows: the "New York Class," the "Arizona Class," the "Arkansas Class," the "California Class," the "Colorado Class," the "Florida Class," the "Iowa Class," the "New Jersey Class," the "Pennsylvania Class," the "Tennessee Class," the "Texas Class," and the "Washington Class"[26]

18. Plaintiffs also seek injunctive relief for the putative "Nationwide Class," which they define as "[a]ll persons, other than Mattel, Inc. and Fisher-Price, Inc., and their employees, who purchased or owned any model of Fisher-Price Rock 'n Play Sleeper in the United States from

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[23] Complaint, ¶¶ 47-50.

[24] Complaint, ¶ 47.

[25] Complaint, ¶¶ 1, 69.

[26] Motion for Class Certification, p. 19.

October 1, 2009 until the date of notice."[27] Plaintiffs also seek to certify a nationwide class that includes only purchasers, which they call the "Nationwide Purchaser Class."[28]

III. SUMMARY OF OPINIONS[29]

19. Based upon my expertise and my review and analysis of the Weir Declaration and evidence available in this matter, in my opinion, Mr. Weir's proposed survey is unreliable as evidence of class-wide damages. Based on his description of his proposed conjoint survey, his proposed survey does not match Plaintiffs' allegations, and does not follow accepted practices for conjoint surveys. These critical flaws render Mr. Weir's proposed survey unreliable for his assignment. Additionally, Mr. Weir's generalized description of his proposed survey is incomplete in numerous ways and fails to demonstrate that his method would provide reliable estimates of willingness to pay.

20. **Mr. Weir's proposed survey does not match Plaintiffs' allegations:** A conjoint survey used in a false advertising matter should isolate the effect of the alleged false advertising. However, Mr. Weir's proposed survey does not match Plaintiffs' allegations. In documents including the Complaint and Motion for Class Certification, Plaintiffs allege that the Rock 'n Play Sleeper is unsafe for infant sleep, and that Defendants knew this but misrepresented it. On the other hand, Mr. Weir's proposed Safety Warning is "This inclined infant sleeper carries the risk of infant fatality or other serious health problems," which fails to describe what Plaintiffs

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[27] Motion for Class Certification, p. 19.

[28] Motion for Class Certification, p. 19.

[29] This section provides a high-level overview of my opinions for the convenience of the reader. My full opinions are provided in this report and associated exhibits.

allege is unsafe about the Rock 'n Play Sleeper.[30] Mr. Weir's proposed Safety Warning therefore does not accurately capture the alleged false advertising related to sleep, and it would lead to unreliable and overstated estimates of diminution in value.

21. **Mr. Weir's proposed survey does not follow accepted practices for conjoint surveys:** Even if Mr. Weir's proposed survey isolated the effect of Plaintiffs' allegations, it does not follow accepted practices for conjoint surveys, and is likely to provide unreliable and overstated willingness to pay (and damages) estimates. Mr. Weir's proposed survey will lead to unrealistic scenarios where respondents must choose between products that are similar in many respects other than the presence or absence of a safety disclosure, a decision they would not make in the actual market. In addition, Mr. Weir incorrectly proposes to compare products with his chosen Safety Warning against products with no safety disclosure at all. As a result, respondents' valuations for products with no disclosure might be overstated relative to their valuation for actual products if they assume that the products without the disclosure carry zero risks. Finally, Mr. Weir's proposed survey artificially focuses respondents' attention on negative features that are not commonly emphasized, including his proposed "Safety Warning," "Risk of Mold," and "Risk of Rocking Mechanism Failure."[31]

22. **Additionally, Mr. Weir's generalized description of his proposed survey is incomplete and insufficient to determine whether his method is additionally unreliable:**

a. Mr. Weir has provided a list of attributes that he testified he plans to use in his proposed survey. However, he has not provided evidence that these attributes

[30] Weir Declaration, Exhibit 3, ¶ 28.

[31] Weir Declaration, Exhibit 3, ¶ 24.

include key purchase drivers. If a conjoint survey does not include key purchase drivers, it is likely to overstate the value of product features.

b. Conjoint analysis also requires clearly defined levels for each attribute, but Mr. Weir has not provided details on the levels of most of the attributes in his proposed survey, or how he would determine those levels. Because Mr. Weir has provided so few details, I generally cannot evaluate either the reliability of the levels of attributes included in Mr. Weir's proposed survey (or his basis thereof), or the method that he would use to determine those levels.

c. Mr. Weir states that he will "pretest" his proposed survey prior to administering it, but does not provide sufficient information about how he would conduct this pretest or use it to alter the final survey.

d. Mr. Weir also does not sufficiently explain the sample population that he is trying to target, or why his target population is reasonable. Mr. Weir is not clear whether he will survey only purchasers of the Rock 'n Play Sleeper, or owners as well. Furthermore, Mr. Weir's proposed survey is not informative about the purchase of used (as opposed to new) products. Mr. Weir also does not appear to limit his proposed survey to respondents who obtained *new* (as opposed to used) products, despite instructing respondents to imagine that they are purchasing a *new* product. Finally, Mr. Weir does not plan to evaluate respondent awareness of the recall or this litigation, which could make their responses unreliable.

e. Mr. Weir also improperly attempts to justify his chosen sample size based on a "rule of thumb" that has been criticized by the very sources he cites in support of it.

23. I reserve the right to modify my opinions and analyses if additional materials or information become available, or if Plaintiffs' experts provide additional opinions or testimony. I further reserve the right to prepare demonstrative exhibits as part of providing testimony.

IV. OVERVIEW OF CONJOINT SURVEYS AND OVERVIEW OF MR. WEIR'S PROPOSED CONJOINT SURVEY

24. In this section, I provide a brief overview of conjoint surveys, which is largely drawn from my published teaching materials from Harvard Business School, and my "Conjoint Analysis" chapter in the *Handbook of Marketing Analytics*.[32] I then provide an overview of Mr. Weir's proposed survey. In Sections V through VII, I summarize and provide the bases for my opinion that Mr. Weir's proposed survey is unreliable for this matter.

A. Overview of Conjoint Surveys

25. Most purchasing decisions in the real world involve trade-offs. For instance, would a consumer buy a premium car with all-wheel drive, or an economy car with better gas mileage? Would a consumer buy a more expensive phone plan with unlimited calls, or a cheaper plan that only includes 500 minutes? Companies must consider these consumer trade-offs when

[32] Copies of my Harvard Business School online tutorial (Elie Ofek and Olivier Toubia, "Conjoint Analysis: Online Tutorial," *Harvard Business School Tutorial*, April 2014) and handbook chapter on "Conjoint Analysis" (Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018) are attached in **Appendix D**. I do not include my Harvard Business School guide on conjoint analysis (Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014) because it is not authorized for copying or posting; it is available for purchase at https://store.hbr.org/product/conjoint-analysis-a-do-it-yourself-guide/515024.

developing new products and services. To help businesses understand how customers make trade-offs among various features, researchers have developed a method of market research called "conjoint analysis." Conjoint analysis is a survey research method for assessing consumer preferences for various attributes of products (or services) in certain circumstances. As described in my chapter on conjoint analysis in the 2018 Handbook of Marketing Analytics,

> [t]he premise of Conjoint Analysis is to decompose a product or service into *attributes* (e.g., "number of minutes included," "number of GB of data," "charge for additional minutes," "base price," etc.) that each has different *levels* (e.g., "500 minutes," "1,000 minutes," "unlimited"). The output of a Conjoint Analysis study is an estimation of how much each consumer in a sample values each level of each attribute.[33]

26. One format of conjoint analysis is "choice-based" conjoint, in which consumers are asked to choose one among a small number of profiles.[34] Profiles are hypothetical products that are described as a bundle of attributes, where each attribute is set at a particular level.[35] For example, in a conjoint survey on cell phone plans, a profile might be a "$100 plan with unlimited calls and 10GB of data per month."[36] Or if the survey dealt with cars, the profiles might be as pictured in Figure 1: the attributes would be "Brand Origin," "Body Type," "Engine Type," and "Price." The levels for "Brand Origin" would be "Japanese," European," or "American"; the levels for "Body Type" would be "Sedan," "SUV," or "Sports Car"; and so on.

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[33] Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018, pp. 52-53 (emphasis in original).

[34] Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018, p. 57.

The main benefit of running a choice-based conjoint survey is that it is "closer to the type of decisions that consumers make in real life" in which they are "choosing one alternative over others." This is as opposed to "ratings-based" conjoint surveys in which respondents rate profiles on some response scale. Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018, pp. 56-57.

[35] Elie Ofek and Olivier Toubia, "Conjoint Analysis: Online Tutorial," *Harvard Business School Tutorial*, April 2014, p. 3.

[36] Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018, p. 53.

Figure 1: Examples of Product Profiles[37]

Profile #	Brand Origin	Body Type	Engine Type	Price
1	Japanese	Sedan	Gasoline	$20,000
2	European	SUV	Gasoline	$40,000
3	American	SUV	Electric	$30,000
4	European	Sports Car	Hybrid	$30,000
5	Japanese	Sports Car	Electric	$40,000

27. Conjoint analysis surveys can vary in many ways, but they all involve three steps:

Step 1. Selecting the attributes and levels for the product profiles to use in the survey.[38]

In this step, researchers must consider: **A)** How many attributes to include. The more attributes that are included, the more complex the profile descriptions become and the more difficult it is for respondents to provide meaningful responses. **B)** Which attributes to include. Generally, the most important and informative attributes will be the ones that "have the potential to sway consumers' choices and can actually be changed or controlled by the firm."[39] **C)** How to define the levels of the attributes. Attributes should be realistic, and should not be subjective or

[37] Elie Ofek and Olivier Toubia, "Conjoint Analysis: Online Tutorial," *Harvard Business School Tutorial*, April 2014, p. 7.

[38] Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018, p. 55.

[39] Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014, p. 2.

ambiguous.[40] **D)** How many levels to assign to each attribute. Attributes should have a similar number of levels (e.g., between two to four levels).[41] **E)** Not to draw artificial focus to certain features, known as a "focusing illusion" or "focalism."[42]

Step 2. Survey implementation and collecting data from a sample of respondents.[43]

Conjoint analysis studies are typically performed online, with a variety of options available for hosting online conjoint analysis surveys.[44] There are also a variety of sources of respondents for online conjoint analysis studies. To ensure the survey results are representative of the target market, the sample of respondents must be "representative of the target market you are addressing," and the products in the study must be "representative of the products potentially available or that would be in the consideration set of the target market."[45] It is generally recommended that researchers conduct a pretest prior to administering their survey, "to increase the likelihood that their questions are clear and unambiguous."[46]

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[40] Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014, p. 2.

[41] Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014, p. 3.

[42] *See, e.g.,* David A. Schkade and Daniel Kahneman, "Does Living in California Make People Happy? A Focusing Illusion in Judgments of Life Satisfaction," *Psychological Science*, Vol. 9, No. 5, 1998, pp. 340-346.

[43] Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018, p. 55.

[44] Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018, p. 59.

[45] Elie Ofek and Olivier Toubia, "Conjoint Analysis: Online Tutorial," *Harvard Business School Tutorial*, April 2014, p. 22. Mr. Weir does not clearly define his target population. *See* Section VII.D for further discussion.

[46] Shari Seidman Diamond, "Reference Guide on Survey Research," *Reference Manual on Scientific Evidence*, 2011, pp. 359-423 at 388.

Step 3. Using the survey results to estimate the impact of the attribute levels on respondents' preferences (which is called their "partworths")[47] and to make inferences about the target market's preferences.[48]

In a choice-based conjoint analysis, typical methods used to derive partworths include logistic regression (which is used to evaluate probabilities among discrete choices), or hierarchical Bayes estimation if a researcher is interested in "providing individual-level estimates of partworths."[49] There are several types of inferences a researcher might make from a conjoint analysis, including "to infer willingness to pay for features of a product or service. This is feasible as long as price is one of the attributes in the survey."[50]

28. If a researcher does not follow accepted practices for each of the steps I outline above and/or fails to avoid certain pitfalls that some researchers fall prey to, the conclusions of a conjoint analysis can be unreliable.

B. Overview of Mr. Weir's Proposed Survey

29. Exhibit 3 of Mr. Weir's declaration vaguely outlines how Mr. Weir might design a proposed survey at some point in the future. Mr. Weir's declaration claims that the attributes in his proposed survey "*might* include Brand, Padding, Frame, Sounds/Vibrations, Risk of Mold, Risk of Rocking Mechanism Failure, Safety Warnings, and Price."[51] Mr. Weir's discussion of his

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[47] "Partworths are the utility of each attribute level. They are called partworths because they capture how much each PART of the product is WORTH to the consumer." Elie Ofek and Olivier Toubia, "Conjoint Analysis: Online Tutorial," *Harvard Business School Tutorial*, April 2014, p. 4.

[48] Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018, p. 55.

[49] Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018, p. 61.

[50] Olivier Toubia, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018, p. 63.

[51] Weir Declaration, Exhibit 3, ¶ 24 (emphasis added). Mr. Weir testified that "[b]arring further evidence, these are the attributes that will be used." Weir Deposition, 275:2-14. This suggests that Mr. Weir intends for his proposed survey to include all of the potential attributes in the Weir Declaration. *See* Section VII.A for further discussion.

proposed sample size suggests that each attribute would have at most six levels, although it is not clear if the largest number of levels would in fact be six or which attribute(s) this would be.[52] The Safety Warning is what Mr. Weir calls his "attribute of interest."[53] It appears it would have two levels: one level with the disclosure, "This inclined infant sleeper carries the risk of infant fatality or other serious health problems," and another level with no disclosure at all.[54]

30. Mr. Weir proposes to use an online survey with a sample of 300 respondents, drawn from an ambiguously-defined population in the U.S.[55] After an initial screening and a series of instructions, respondents would be presented with 13 choice tasks.[56] For each choice task, respondents would choose among three products.[57] For his proposed survey, it appears that Mr. Weir would use a sample vendor such as Dynata and would use the Sawtooth Software survey system to administer and collect data.[58] Mr. Weir provides a vague outline of a pretest he would conduct on approximately 50 respondents prior to fielding his proposed survey.[59] Mr. Weir would obtain partworth estimates using "Hierarchical Bayes regression analysis."[60]

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[52] Weir Declaration, Exhibit 3, ¶ 33 (performing a calculation intended to determine the required sample size assuming that the largest number of levels for any attribute will be six). Mr. Weir has provided no further information on the number of levels he will use for most of his attributes. *See* Section VII.B for further discussion.

[53] Weir Declaration, Exhibit 3, ¶ 25.

[54] Weir Declaration, Exhibit 3, ¶ 28; Weir Deposition, 287:4-13, 287:19-288:10. As I discuss below in Section V, Mr. Weir's proposed Safety Warning does not match Plaintiffs' allegations, which renders his proposed survey unreliable as evidence of damages.

[55] Weir Declaration, Exhibit 3, ¶¶ 21-22, 33-34. As I discuss below in Section VII.D, it is unclear whether Mr. Weir intends to target purchasers or both purchasers and users of the Rock 'n Play Sleeper.

[56] Weir Declaration, Exhibit 3, ¶¶ 21, 23-29.

[57] Weir Declaration, Exhibit 3, ¶ 29.

[58] Weir Declaration, Exhibit 3, ¶¶ 35-36.

[59] Weir Declaration, Exhibit 3, ¶¶ 31-32. As I discuss in Section VII.C, Mr. Weir does not provide any specifics about how he would conduct this pretest and therefore has not provided sufficient information for me to evaluate how his "pretest" would impact the reliability of his final survey.

[60] Weir Declaration, Exhibit 3, ¶ 37.

V. MR. WEIR'S PROPOSED CONJOINT SURVEY DOES NOT MATCH PLAINTIFFS' ALLEGATIONS, AND IS THEREFORE UNRELIABLE AS EVIDENCE OF CLASS-WIDE DAMAGES

31. A damages expert in litigation should calculate only damages attributable to Plaintiffs' allegations, assuming that defendants are found liable.[61] Similarly, a conjoint survey used as an input to damages in a false advertising matter should isolate the effect of the alleged misrepresentations and/or omissions. Mr. Weir's proposed survey does not match Plaintiffs' allegations. As a result, Mr. Weir's proposed survey is unreliable as evidence of damages.

32. To determine the diminution in value of the Rock 'n Play Sleeper, Mr. Weir proposes to use the results of his conjoint survey to compare consumer preferences for a product with his chosen Safety Warning to a product with no safety disclosure at all. In particular, Mr. Weir describes his diminution in value measure as follows:

> I will have the market simulator compare two Rock 'n Play Products that are identical in all respects except that one does not disclose the safety risk of the Rock 'n Play while the other makes plain the alleged truth about such risks. I would then use the market simulator to simulate a condition where the price of the second product is reduced to the level where both products obtain equal market share. … The diminution in value equals the difference between the two prices that compensates for the understanding of the true risks of the Rock 'n Play.[62]

33. As Mr. Weir's declaration sets out, his proposed survey will present each respondent with 13 choice tasks. Each choice task will include "three sleepers with the attributes as presented to

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[61] *See, e.g.,* Mark A. Allen, Robert E. Hall, and Victoria A. Lazear, "Reference Guide on Estimation of Economic Damages," *Reference Manual on Scientific Evidence*, 2011, pp. 425-502 at 432 (emphasis in original): "The first step in a damages study is the translation of the legal theory of the harmful event into an analysis of the economic impact of that event… a proper construction of the but-for scenario and measurement of the hypothetical but-for plaintiff's value by definition includes in damages only the loss *caused* by the harmful act."

[62] Weir Declaration, Exhibit 3, ¶ 49.

respondents, and varying levels."[63] According to Mr. Weir, his "Safety Warning" is the attribute of interest.[64]

34. In addition, in Mr. Weir's proposed market simulation, only the "Safety Warning" attribute and price differ between the two products. In particular, the product with no safety disclosure at all corresponds to Mr. Weir's portrayal of the actual Rock 'n Play Sleeper, while the product with his chosen Safety Warning corresponds to his portrayal of the but-for world Rock 'n Play Sleeper.[65] As a result, the Safety Warning attribute is the key measure that forms the basis of Mr. Weir's subsequent "% Diminution in Value Factor" damages.[66] Thus, to measure damages attributable to the allegations in this matter, Mr. Weir's Safety Warning attribute *must* properly reflect Plaintiffs' allegations.

35. In particular, I understand that Plaintiffs allege that the Rock 'n Play Sleeper is "unsuitable for infant sleep," including overnight and prolonged sleep, and that Defendants knew this but misrepresented it.[67] I summarize Plaintiffs' allegations, as reflected in documents such as the Complaint and Motion for Class Certification, above in Section II.B.

36. The Weir Declaration, on the other hand, sets out Mr. Weir's proposed Safety Warning as "This inclined infant sleeper carries the risk of infant fatality or other serious health problems."[68]

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[63] Weir Declaration, Exhibit 3, ¶ 29.

[64] Weir Declaration, Exhibit 3, ¶ 25.

[65] Weir Declaration, Exhibit 3, ¶ 49: "For the market simulation, I will have the market simulator compare two Rock 'n Play Products that are identical in all respects except that one does not disclose the safety risk of the Rock 'n Play while the other makes plain the alleged truth about such risks."

[66] Weir Declaration, Exhibit 3, ¶ 59.

[67] Complaint, ¶¶ 1, 2.

[68] Weir Declaration, Exhibit 3, ¶ 28.

Mr. Weir's Safety Warning does not describe what Plaintiffs allege is unsafe about the Rock 'n Play Sleeper that Defendants allegedly did not disclose. Mr. Weir provides no basis in his declaration for his chosen Safety Warning. In fact, Mr. Weir's chosen Safety Warning conflicts his declaration's summary of Plaintiffs' allegations.[69]

37. When asked in his deposition, Mr. Weir testified that he based his Safety Warning language on "…plaintiffs' theory of liability and a review of the recall disclaimer language that accompanied the recall of this product."[70] However, Mr. Weir's declaration and testimony neither cite any specific document(s) or language on which he based his Safety Warning nor explain why his Safety Warning is appropriate in light of these unspecified documents. For these reasons, there is no support for the purported basis for Mr. Weir's Safety Warning.[71]

38. Mr. Weir's explanation in deposition, wherein he stated that he believes Plaintiffs' theory of liability is that the Rock 'n Play Sleeper is unsafe for all purposes, not just sleep,[72] suggests that he believes a broadly defined key survey attribute is appropriate. Mr. Weir's presumed beliefs and his proposed Safety Warning, however, are not linked to Plaintiffs' allegations as reflected in the Complaint, Motion for Class Certification, and Plaintiffs' counsel's statements at a hearing (or even to the Weir Declaration's summary of those allegations); therefore they do not accurately capture the alleged false advertising related to sleep.[73]

[69] Weir Declaration, ¶¶ 5, 9 (which I excerpt above in Section II.B).

[70] Weir Deposition, 269:8-22.

[71] To the extent that Mr. Weir's Safety Warning is based on language from the recall, Mr. Weir also has not explained why, as a general matter, using the language from a recall would be a reasonable method in evaluating consumers' preferences for alleged false advertising related to any issues that led to that recall.

[72] Weir Deposition, 141:12-15; *see also* 147:20-25 ("I would defer to plaintiffs' papers, but it's my understanding that they [Plaintiffs] do not believe the product is safe for any use.").

[73] I summarize Plaintiffs' allegations as reflected in these documents in Section II.B.

39. When confronted with choice tasks that include product profiles with Mr. Weir's Safety Warning, respondents would reasonably assume that Mr. Weir's Safety Warning describes a product that has safety risks for any use. Respondents to Mr. Weir's proposed survey would have no basis to ascribe the risks Mr. Weir suggests are present in the product to the at-issue feature of sleep. If survey respondents assume that Mr. Weir's Safety Warning describes a product that has safety risks for any use, but in fact the safety risks are only for use in sleep, this would lead to unreliable and overstated estimates of diminution in value associated with the Safety Warning. The diminution in value would be overstated because the Rock 'n Play Sleeper has non-sleep uses for which Mr. Weir's Safety Warning would not apply.

40. Indeed, the testimony of the named Plaintiffs indicates that the Rock 'n Play Sleeper had non-sleep uses. I received and reviewed the deposition transcripts of 21 named Plaintiffs, 19 of whom used the Rock 'n Play Sleeper themselves.[74] Of these 19 named Plaintiffs who used the Rock 'n Play Sleeper, 17 used it for non-sleep uses. For example, Megan Kaden testified that "[i]f I had something that I had to do and needed a safe place for her, I may put her [in the Rock 'n Play Sleeper] for a few minutes," and Joshua Nadel testified "[m]aybe I was watching TV and the baby would be next to me in the Rock 'n Play just hanging out."[75] See **Exhibit 1.**

[74] Two named Plaintiffs, Karen Flores and Rebecca Drover, purchased the product for someone else as a gift, but did not use the product themselves. *See* **Exhibit 1**.

[75] Deposition of Megan Kaden, April 15, 2021, 155:1–6; Deposition of Joshua Nadel, April 13, 2021, 84:20–85:2.

VI. MR. WEIR'S PROPOSED CONJOINT SURVEY ALSO DOES NOT FOLLOW ACCEPTED PRACTICES FOR CONJOINT SURVEYS, AND IS LIKELY TO PROVIDE UNRELIABLE AND OVERSTATED DAMAGES ESTIMATES

41. As discussed above, the conjoint survey methodology is a market research tool that was developed to measure the value consumers place on product features within a *realistic* purchase environment.[76] Mr. Weir's proposed survey would pose hypotheticals that would never be present in the marketplace. In particular, his proposed survey could ask respondents to imagine products that vary on whether they carry a disclosure of a risk of infant fatality or other serious problem, holding almost everything else constant.[77] As I discuss below, Mr. Weir's proposed survey does not follow accepted practices for conjoint surveys, and thus would provide unreliable and overstated estimates.

A. Mr. Weir's Proposed Survey Is Not an Accepted Use of Conjoint Survey Methodology, It Would Lead to Unrealistic Scenarios, and His Estimates Would Be Unreliable for Damages

42. As a general matter, the more a conjoint survey differs from actual purchase decisions, the less reliable it is.[78] Mr. Weir's proposed survey will require giving respondents unrealistic choices. In particular, consumers do not regularly choose between products that are similar in many respects other than the presence or absence of a safety disclosure. Yet Mr. Weir's proposed

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[76] As I state in my Online Tutorial, "It is important that these product profiles represent offerings that may be available on the market or that don't seem infeasible or unrealistic to offer." Elie Ofek and Olivier Toubia, "Conjoint Analysis: Online Tutorial," *Harvard Business School Tutorial*, April 2014, p. 7. *See also, e.g.,* the Sawtooth Software website, which states, "It mimics the tradeoffs people make in the real world when making choices." "What is Conjoint Analysis?," Sawtooth Software, https://sawtoothsoftware.com/conjoint-analysis.

[77] Mr. Weir contends that the Safety Warning that he would include in his proposed survey is "This inclined infant sleeper carries the risk of infant fatality or other serious health problems." Weir Declaration, Exhibit 3, ¶ 28.

[78] *See, e.g.,* Moshe Ben-Akiva, Daniel McFadden, and Kenneth Train, "Foundations of Stated Preference Elicitation: Consumer Behavior and Choice-based Conjoint Analysis," *Foundations and Trends in Econometrics*, Vol. 10, No. 1-2, 2019, pp. 1-144 at 26: "The goal of a conjoint study designed for prediction should be to anticipate and mimic the training that real markets provide."

survey asks respondents to choose between such products.[79] In particular, his "Safety Warning" attribute will ask respondents to imagine that products may vary only on the presence or absence of a safety disclosure, while holding all other attributes constant (e.g., brand and functionalities). Given this stark choice, respondents are unlikely to accurately trade off the presence of a disclosure about a risk of infant fatality against other attributes. Mr. Weir's proposed survey is not consistent with standard practices and will likely create overstated willingness to pay for Mr. Weir's proposed Safety Warning among many respondents, which will result in overstated damages estimates.[80]

43. Further, in his declaration, Mr. Weir states that conjoint analysis has been used in a litigation setting to estimate values for features of products. Mr. Weir's declaration, however, does not address use of conjoint survey methods for matters related to his proposed survey *in this case*. In particular, Mr. Weir describes applications of conjoint analysis to "determine 'whether health claims (claims of health-promoting effects) of food products positively influence product price and consumer choices,'" "to estimate the relative contribution of declared amounts of different nutrients to the perception of the overall 'healthfulness' of foods by the consumer," and "to evaluate which attributes of orange juice consumers value most."[81] But Mr. Weir has not

[79] Weir Declaration, Exhibit 3, ¶ 28.

[80] By "overstated willingness to pay for Mr. Weir's proposed Safety Warning," I mean that a respondent's valuations for a product with no safety disclosure are overstated relative to their valuations for a product with Mr. Weir's proposed Safety Warning.

[81] Weir Declaration, Exhibit 3, ¶¶ 8-10. *See* Mitsunori Hirogaki, "Estimating Consumers' Willingness to Pay for Health Food Claims: A Conjoint Analysis," *International Journal of Innovation, Management and Technology*, Vol. 4, No. 6, 2013, pp. 541-546; Adam Drewnowski, Howard Moskowitz, Michele Reisner, and Bert Krieger, "Testing consumer perception of nutrient content claims using conjoint analysis," *Public Health Nutrition*, Vol. 13(5), 2010, pp. 688-694; and Izabel Gadioli et al., "Evaluation of Packing Attributes of Orange Juice on Consumers' Intention to Purchase by Conjoint Analysis and Consumer Attitudes Expectation," *Journal of Sensory Studies*, Vol. 28, pp. 57-65.

provided examples of conjoint analysis involving the presence or absence of safety disclosures, as is the case in his proposed survey, and his proposed survey is not appropriate in this context in my view.[82]

B. Mr. Weir Incorrectly Proposes to Compare Products With His Chosen Safety Warning and Ones With No Safety Disclosure at All

44. A further error with Mr. Weir's proposed survey is that each product without his chosen Safety Warning would have no safety disclosure at all.[83] This would create a false dichotomy for respondents, who will contrast the products in the survey that do and do not include Mr. Weir's Safety Warning (which is, "This inclined infant sleeper carries the risk of infant fatality or other serious health problems"[84]). Respondents might infer that the products with no safety disclosure carry *no* risk of infant fatality or serious health problems. However, Mr. Weir does not provide any evidence that it would be realistic for respondents to infer that the products with no safety disclosure carry no such risk.

45. If respondents to Mr. Weir's proposed survey believe that products with no safety disclosure carry no risk of infant fatality or serious health problems, but actual products in fact carry such risks, then respondents' valuations for products with no safety disclosure would be overstated relative to their valuation for actual products. In turn, Mr. Weir's willingness to pay

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[82] Mr. Weir cited three conjoint analyses which involve the presence or absence of health claims, *not* safety disclosures. Weir Declaration, Exhibit 3, ¶¶ 8-10. For example, Hirogaki (2013) conducted a conjoint analysis on green tea and found that health claims had a significant effect on price. Mitsunori Hirogaki, "Estimating Consumers' Willingness to Pay for Health Food Claims: A Conjoint Analysis," *International Journal of Innovation, Management and Technology*, Vol. 4, No. 6, 2013, pp. 541-546.

While these studies demonstrate that it may be reasonable to compare similar products with or without health claims, they have no relation to Mr. Weir's proposal to compare similar products with or without safety disclosures.

[83] Weir Deposition, 287:4-13, 287:19-288:10. *See also* Weir Declaration, Exhibit 3, ¶ 28.

[84] Weir Declaration, Exhibit 3, ¶ 28.

estimates related to the safety disclosure would also be overstated and unreliable.[85] Mr. Weir does not explain how he intends to ensure that respondents correctly interpret his "Safety Warning" attribute and make appropriate comparisons between products with and without his Safety Warning.

C. Mr. Weir's Proposed Survey Focuses Respondents' Attention on Negative Features, Which Is Likely to Lead to Overstated Valuations for These Features and Unreliable Results

46. Academic marketing literature finds that exposing respondents to features that they do not consider in the actual purchase environment can lead to overstated WTP valuations.[86] Mr. Weir provides no evidence that consumers deciding which baby products to purchase consider safety disclosures and differentiate between products based on safety disclosures. By forcing the respondents in his proposed survey to focus on negative features related to safety disclosures and safety risks in their hypothetical purchase decisions, Mr. Weir primes them to think about safety disclosures and risks more than they would under normal purchasing conditions.[87] This priming is likely to cause respondents to make choices that would not reflect

[85] Mr. Weir's estimate of willingness to pay is based on how respondents to his proposed survey value a product with his Safety Warning, compared to a product with no safety disclosure at all. Weir Declaration, Exhibit 3, ¶ 49. If respondents overvalue the product with no safety disclosure at all, this will cause Mr. Weir to overestimate any reduction in value due to his Safety Warning.

[86] In general, respondents who focus too much on certain features can overestimate the impact of those features. *See, e.g.,* David A. Schkade and Daniel Kahneman, "Does Living in California Make People Happy? A Focusing Illusion in Judgments of Life Satisfaction," *Psychological Science*, Vol. 9, No. 5, 1998, pp. 340-346. This study found that when asked to compare life in California to life in the Midwest, Californians and Midwesterners placed their focus on climate differences. As a result, the participants incorrectly predicted that life would be better in California than in the Midwest. In fact, other features like job prospects or social life were more important determinants of life satisfaction.

[87] As I describe below, three of Mr. Weir's proposed eight features are negative ones.

their real-world behavior, which in turn will cause Mr. Weir's estimates of valuations related to the alleged false advertising to be overstated.

47. Mr. Weir does not discuss this important survey design challenge or how he might mitigate it. As a result, it is unlikely that his proposed survey can overcome this artificial focus on a feature of interest ("focusing illusion" or "focalism") that is likely to cause respondents' valuation of the feature at issue to be overstated.[88]

48. Academic research has also demonstrated that WTP valuations are highly dependent on the way that information is framed in a survey.[89] When including a negative feature that is not commonly emphasized, such as a safety disclosure, it will be difficult to avoid having respondents place an artificially large focus on that feature. The Weir Declaration's list of potential features includes two additional negative features besides the Safety Warning condition at issue: "Risk of Mold" and "Risk of Rocking Mechanism Failure."[90] This priming to consider

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[88] For example, one academic article summarizes focalism as follows: "Research in psychology has shown that people tend to overweight whatever information is most salient or most accessible at a particular moment and neglect other relevant considerations." Gerald Haubl, Benedict Dellaert, and Bas Donkers, "Tunnel Vision: Local Behavioral Influences on Consumer Decisions in Product Search," *Marketing Science*, Vol. 29, No. 3, September 22, 2009, pp. 438-455 at 441.

This flaw in Mr. Weir's proposed survey is likely to be exacerbated because Mr. Weir does not provide any evidence that the attributes included in his survey are key purchase drivers for the Rock 'n Play Sleeper or competitive products. I discuss this issue further in Section VII.A.

[89] *See, e.g.,* Amos Tversky and Daniel Kahneman, "The Framing of Decisions and the Psychology of Choice," *Science*, Vol. 211, No. 4481, 1981, pp. 453-458 at 453; Amos Tversky and Daniel Kahneman, "Choices, Values, and Frames," *American Psychologist*, Vol. 39, No. 4, 1984, pp. 341-350; Kenneth Arrow et al., "Report of the NOAA Panel on Contingent Valuation," January 11, 1993, pp. 19-20.

The importance of clear and neutral framing is consistent with the general principles of survey research. For instance, the Reference Guide on Survey Research explains that "When unclear questions are included in a survey, they may threaten the validity of the survey by systematically distorting responses if the respondents are misled in a particular direction…" Shari Seidman Diamond, "Reference Guide on Survey Research," *Reference Manual on Scientific Evidence*, 2011, pp. 359-423 at 388. *See also* Jon A. Krosnick and Stanley Presser, "Question and Questionnaire Design," Bingley, UK, Emerald Group Publishing Limited, 2010" in Handbook of Survey Research, edited by Wright, James D., and Peter V. Marsden. (2010): 263-313 at 264.

[90] Weir Declaration, Exhibit 3, ¶ 24. In his deposition, Mr. Weir testified that "[b]arring further evidence, these are the attributes that will be used." Weir Deposition, 275:2-14.

negative features of the product is likely to impact his estimates of the alleged false advertising. By including three negative features (risk of mold, risk of rocking mechanism failure, and Safety Warning) in his proposed survey, Mr. Weir's design focuses respondents on features they might not usually pay attention to prior to the survey, introducing focalism bias. Of Mr. Weir's seven potential non-price features, three of them relate to things that could go wrong with the product, all of which will presumably be presented as potential health hazards. Asking respondents to think about several hazards is likely to make their choices more risk averse. In addition, having so many negative features increases the differences between this choice exercise and respondents' real-world purchase decisions.

VII. PUTTING THOSE CRITICAL FLAWS ASIDE, WHICH THEMSELVES MAKE MR. WEIR'S PROPOSED SURVEY UNRELIABLE, MR. WEIR'S GENERALIZED DESCRIPTION OF HIS PROPOSED SURVEY IS INCOMPLETE AND INSUFFICIENT TO DETERMINE WHETHER HIS METHOD IS ADDITIONALLY UNRELIABLE

49. Mr. Weir has not provided critical information about his proposed survey, including, among others, the selection of attributes and levels, sample selection, and planned pretest. Mr. Weir's description of his proposed survey in his declaration and testimony is insufficient to determine if his methodology would provide reliable estimates of willingness to pay.[91]

[91] In addition, Mr. Weir's list of documents that he reviewed is insufficient to determine if his opinions have any basis in these documents. The Weir Declaration states that "[t]he documents, data and other materials that I relied upon in forming my opinions are identified throughout my report and in Exhibit 2, attached hereto." Weir Declaration, ¶ 7.

Exhibit 2 in the Weir Declaration ("Documents Reviewed") lists 80 unique Bates-stamped documents as well as website domain names that include: fisher-price.com, mattel.com, archive.org, buybuybaby.com, target.com, walmart.com, and amazon.com. The 80 Bates-stamped documents include 17 PDFs, which comprise 681 pages in total, 58 Excel files, 2 CSV files, and 3 PowerPoint files. However, the Weir Declaration does not specifically cite to either **1)** any of these 80 Bates-stamped documents or **2)** any specific web pages from the domain names that I list above. As a result, Mr. Weir's Exhibit 2 is insufficient to allow evaluation of whether his opinions have any basis in these documents, and hence whether his opinions are reliable.

A. Mr. Weir Has Not Provided Evidence That the Attributes in His Proposed Survey Will Include Key Purchase Drivers, the Lack of Which Is Likely to Lead to Overstated Valuations

50. Mr. Weir has not provided any basis to evaluate his selection of features for his proposed survey.[92] Mr. Weir also has not provided any evidence that these features are the key purchase drivers for the Rock 'n Play Sleeper or competitive products. In discussing Mr. Weir's feature selection, the Weir Declaration states that "[t]he attribute of interest is the Safety Warning. The other attributes are distractor attributes, and will be selected to be believable and understandable."[93] Contrary to the Weir Declaration, conjoint survey attributes besides price and the attribute of interest are not just "distractors" that need only to be "believable and understandable." The other survey attributes also need to include the key purchase drivers. If Mr. Weir's proposed attributes do not include the key purchase drivers, this would likely cause his willingness to pay calculations to be overstated.

51. A key principle of conjoint analysis is that respondents should "hold constant" all features besides the ones included in the choice task. Consistent with this, Mr. Weir states that his proposed survey will instruct respondents to assume that "[a]ny features not shown in the exercise" are "the same across the possible choices presented."[94] However, if a conjoint survey

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Mr. Weir testified that he "looked at each" Fisher-Price Bates-stamped document listed in Weir Declaration Exhibit 2. Weir Deposition, 157:22-158:2. There are 24 such documents (as indicated by the Bates prefixes of the files). Mr. Weir's testimony did not indicate which of these documents or portions thereof he believes support which of his opinions. Therefore, this testimony is insufficient to allow evaluation of whether Mr. Weir's opinions have any basis in these 24 documents.

[92] I use the terms "attribute" and "feature" interchangeably.

[93] Weir Declaration, Exhibit 3, ¶ 25. In Mr. Weir's proposed survey, the inclusion of Mr. Weir's Safety Warning is the only difference between a product that Mr. Weir claims corrects the alleged false advertising in this matter and an otherwise identical product that Mr. Weir claims does not correct the alleged false advertising. *See* Weir Declaration, Exhibit 3, ¶ 49.

[94] Weir Declaration, Exhibit 3, ¶ 23. Mr. Weir also plans to instruct respondents to assume that "all of the sleepers are of the same durability, and have the same warranty." Weir Declaration, Exhibit 3, ¶ 23. While Mr. Weir plans to

does not include important features of the products studied, then it is harder for respondents to follow instructions to "hold constant" all other features. As Allenby et al. (2014) state:

> [I]f one of the hypothetical products in the choice task has a very high price, it is unlikely that the respondents will hold constant other features. Their natural inclination is to assume that, perhaps, the high price indicates that this hypothetical product has very important features that are missing from the alternatives. This violation of the hold-constant instruction is much less likely if other important features are included in the conjoint survey design.[95]

52. This advice to include the important features in the choice task is consistent with other academic resources on conjoint analysis. For example, prominent conjoint researcher Vithala R. Rao explains that a conjoint study requires an understanding of "salient attributes involved in the choice of an alternative by a majority of target consumers."[96] Similarly, an academic article providing an overview of conjoint research states that "at the end of the day a large fraction of the success of conjoint rests on the researcher's ability to identify the salient attributes and

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provide these direct instructions about durability and warranty, he does not plan to instruct respondents about whether they should assume that the safety risks of the products in his proposed survey differ.

[95] Greg M. Allenby, Jeff Brazell, John R. Howell, and Peter E. Rossi, "Valuation of Patented Product Features," *The Journal of Law & Economics*, Vol. 57, No. 3, August 2014, pp. 629-663 at 642. *See also* Vithala R. Rao and Henrik Sattler, "Measurement of Price Effects with Conjoint Analysis: Separating Informational and Allocative Effects of Price," *Conjoint Measurement: Methods and Applications*, Berlin, Springer, 2007, pp. 31-46 at 42-43, which describes this issue, and states that "[o]ne way to overcome this confounding problem at least partly is to include most of the salient product attributes in the conjoint study."

If respondents assume that higher-priced products have important positive features that are missing from lower-priced alternatives, this will incorrectly reduce their price sensitivity. This occurs because respondents would implicitly offset a higher price by positive attributes not included in the choice task. If price sensitivity is understated, this will cause Mr. Weir's willingness to pay calculations (which inherently are in dollars) to be overstated, which would also cause his damages calculations to be overstated. *See, e.g.,* a Sawtooth Software technical paper, which states: "if respondents spend survey dollars too liberally, this will make their utility for price too small and it will exaggerate their apparent willingness to pay for product features." Bryan K. Orme and Keith Chrzan, "Becoming an Expert in Conjoint Analysis: Choice Modeling for Pros," 2017, p. 195.

[96] Vithala R. Rao, *Applied Conjoint Analysis*, Springer, 2014, p. 43.

levels."[97] My own published teaching materials for Harvard Business School explain that the researcher should either include the most important attributes as part of the choice set or specify the level of those attributes.[98]

53. The Weir Declaration identifies attributes that *might* be included in Mr. Weir's proposed survey. In particular, the Weir Declaration states:

> [R]espondents will be introduced to the attributes that will be included in the choice exercises. These attributes might include Brand, Padding, Frame, Sounds/Vibrations, Risk of Mold, Risk of Rocking Mechanism Failure, Safety Warnings, and Price.[99]

54. In his deposition, however, Mr. Weir testified that "[b]arring further evidence, these are the attributes that will be used."[100] This suggests that Mr. Weir intends to include all of his potential attributes in his proposed survey. However, Mr. Weir provides no explanation why it is reasonable to use eight attributes. In fact, using too many attributes can cause the results of a conjoint survey to be unreliable. The more attributes that are included, the more complex the profile descriptions become and the more difficult it is for respondents to provide meaningful responses, which is why experts recommend selecting no more than six attributes:

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[97] Eric T. Bradlow, "Current Issues and a 'Wish List' for Conjoint Analysis," *Applied Stochastic Models in Business and Industry*, Vol. 21, No. 4-5, 2005, pp. 319-323 at 322.

[98] If there is a must-have feature that consumers absolutely need and expect (e.g., blue tooth for a mobile phone), collecting additional data on that feature may not necessarily be informative, so there is no need to include the feature as an attribute. In these instances, the researcher should still tell respondents what value they should assume these must-have features will take. Otherwise, consumers will make assumptions on these features, which can affect their responses. Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014, p. 2.

In contrast, Mr. Weir's proposed survey will ask respondents to "Assume that all of the sleepers are of the same durability, and have the same warranty" without explaining the level of durability or warranty that respondents should assume. Weir Declaration, Exhibit 3, ¶ 23.

[99] Weir Declaration, Exhibit 3, ¶ 24.

[100] Weir Deposition, 275:2-14.

> Experts usually recommend keeping the number of attributes at or below 6. Keep in mind that conjoint analysis is a demanding task for consumers. Increasing the number of attributes increases the burden on consumers in at least two ways: (i) it creates a need for longer questionnaires (i.e., more data are required to estimate preferences for a longer list of attributes because more parameters need to be estimated), (ii) it makes each question harder to answer, because products become more difficult to evaluate. Unfortunately, when tired or bored, respondents are likely to answer questions randomly or by using simplifying heuristics that do not reflect how they would make real-life decisions, thereby biasing the output and rendering any conclusions based on the study potentially misleading.[101]

55. More importantly, the Weir Declaration does not discuss how Mr. Weir identified his list of potential attributes, other than to say, "[t]he attribute of interest is the Safety Warning. The other attributes are distractor attributes, and will be selected to be believable and understandable."[102] The Weir Declaration also does not discuss how Mr. Weir would decide among these attributes (if he does not use all of them, as he testified that he would do).[103]

56. There are various ways through which survey designers could learn about features that are salient to consumers.[104] The Weir Declaration, however, does not propose to use or describe having used any particular methods. Mr. Weir testified that he determined these features by "a review of the products internal documents from Fisher-Price looking at the products on the

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[101] Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014, p. 2.

[102] Weir Declaration, Exhibit 3, ¶ 25. Mr. Weir states that "Brand will always be shown first, and price will always be anchored last," suggesting that brand and price will be attributes included in his proposed survey. Weir Declaration, Exhibit 3, ¶ 29.

[103] Weir Deposition, 275:2-14 ("[b]arring further evidence, these are the attributes that will be used.").

[104] Vithala R. Rao, *Applied Conjoint Analysis*, Springer, 2014; Paul E. Green, Abba M. Krieger, and Yoram (Jerry) Wind, "Thirty Years of Conjoint Analysis: Reflections and Prospects," *Interfaces*, Vol. 31, No. 3, 2001, pp. S56-S73 at S57. My published teaching materials explain that preliminary research is often necessary to determine which attributes are important to consumers' purchase decisions, especially if the researcher has little experience in the category. Elie Ofek and Olivier Toubia, "Conjoint Analysis: Online Tutorial," *Harvard Business School Tutorial*, April 2014, p. 6.

websites, looking at real world marketplace data."[105] However, the Weir Declaration and Mr. Weir's testimony do not specify which documents he looked at to make this determination, nor does he provide any detail on the steps he took to conduct his research or how he arrived at this list of attributes.[106] Therefore, it is not possible to evaluate Mr. Weir's basis for using these attributes, and he has failed to demonstrate that his methodology is reliable.

57. Internal documents from Fisher-Price indicate that Rock 'n Play Sleepers had a variety of attributes. The product was designed to be portable and machine-washable, and it attached toys for a baby to play with.[107] Some Rock 'n Play Sleepers also included attributes such as: a projection light show to entertain babies, an automatic rocking feature to soothe babies, and the ability to control the product with a smart device.[108] These documents are consistent with testimony from Defendants' corporate designee,[109] who stated that the attributes of the product included "the rocking features, folding, portability, washability, [and] a toy for play."[110] Mr. Weir does not provide any rationale for why his proposed survey does not include these attributes.[111]

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[105] Weir Deposition, 273:21-25.

[106] Mr. Weir's Exhibit 2 ("Documents Reviewed") lists 80 Bates-stamped documents as well as the following websites: fisher-price.com, mattel.com, archive.org, buybuybaby.com, target.com, walmart.com, and amazon.com (but not any specific web pages from these domain names). As a result, it is not possible to determine which documents, webpages, or portions thereof Mr. Weir relied on to reach these conclusions.

[107] *See, e.g.* "Voice of the Consumer Baby Gear," 2013, FSHR0059256-FSHR0059277 at 262, and "Baby Gear Spring 2016," FSHR0059366-FSHR0059439 at 413-415.

[108] FSHR0060073-FSHR0060084 at 082-084, and "Baby Gear Spring 2016," FSHR0059366-FSHR0059439 at 417.

[109] Deposition of Sarah Ford, December 11, 2020 ("Ford Deposition"), 12:11-15:5.

[110] Ford Deposition, 99:8-12. *See also* Ford Deposition, 178:19-180:21.

[111] As I discussed above, researchers should either include the important attributes of a product as part of the choice set or specify the level of those attributes. Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014, p. 2.

58. Further, the Weir Declaration discusses "exploratory research" that Mr. Weir plans to do prior to conducting his proposed survey to identify key purchase drivers:

> Prior to completing the design and conducting the conjoint survey, I would conduct in-depth cognitive interviews with purchasers of the Rock 'n Play Products. These cognitive interviews are a type of qualitative research, similar to focus groups, but better suited for the conjoint survey task.
>
> These interviews will permit me to understand background information helpful to developing the conjoint survey. I would conduct approximately eight in-depth telephone interviews of approximately 30 minutes in duration. I would seek background information on what product features drive purchasing behavior for purchasers of Rock 'n Play Sleepers. The participants in the interviews would be purchasers or users of one or more Rock 'n Play Products during the proposed class period.
>
> From these cognitive interviews, I would gain a better understanding of the drivers of consumer choices underlying sleeper purchases that would aid my final design of the conjoint survey.
>
> In addition to the interviews, I would also review available discovery documents produced over the course of this litigation.
>
> In addition, I would also review publicly available sources, such as the website of Defendant Fisher Price, other competing brand websites, and retailer websites.[112]

59. As I discuss above, the attributes in a conjoint survey should include key purchase drivers. Therefore, it is inappropriate for Mr. Weir to have already chosen the attributes that he plans to use in his conjoint survey prior to doing the research to determine which product attributes are key purchase drivers. In addition, Mr. Weir does not provide any details about how these eight interviews would be conducted, or why it is appropriate to conduct only eight

[112] Weir Declaration, Exhibit 3, ¶¶ 14-18.

interviews to understand "what product features drive purchasing behavior for purchasers of Rock 'n Play Sleepers."[113]

60. Although Mr. Weir says he plans to conduct exploratory research, he testified that he has not yet done any such research.[114] Despite this, Mr. Weir testified that his exploratory research is unlikely to result in meaningful changes:

> When I have experience of doing careful conjoint design whether by myself or with other folk, it is often the case that a carefully designed conjoint as I have set forth here will experience few or no changes as a result of the exploratory research that confirms the careful research that was done before.[115]

61. As I discuss throughout this report, there are many crucial omissions in Mr. Weir's proposed survey, and he does not provide evidence in support of many of the aspects of his proposed survey.

B. Conjoint Analysis Requires That the Levels of Attributes Be Clearly Defined, but Mr. Weir Has Not Provided Details on the Levels of the Attributes in His Proposed Survey, or How He Would Determine Those Levels

62. For a conjoint analysis to be reliable, the attributes/features included and the levels of those attributes/features need to be specific, with quantification whenever possible. This is emphasized in the peer-reviewed and technical literatures. Mr. Weir's declaration and testimony do not provide sufficient detail to evaluate whether the potential attributes/features in his proposed survey have been or will be chosen in a reliable way.

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[113] Weir Declaration, Exhibit 3, ¶ 14.

[114] Weir Deposition, 275:15-19.

[115] Weir Deposition, 276:1-7.

63. Academic literature has found that conjoint analysis surveys are more reliable when product features and levels are realistic, clear, and complete.[116]

64. Technical papers by Sawtooth Software, the company whose software Mr. Weir proposes to use,[117] also make similar points. One Sawtooth Software technical paper states that "[d]efining proper conjoint attributes and levels is arguably the most fundamental and critical aspect of designing a good conjoint study."[118] Sawtooth Software warns against incomplete descriptions of feature levels: "[Attribute levels] should be concise statements with concrete meaning. Avoid using ranges to describe a single level of an attribute, such as 'weighs 3 to 5 kilos.' Rather than leave the interpretation to the respondent, it would be better to specify 'weighs 4 kilos.'"[119] Sawtooth Software recommends specific, quantitative language: "Levels such as 'superior performance' also leave too much in question. What does 'superior performance' mean? Try to use specific language to quantify (if possible) the exact meaning of the level."[120]

65. Similarly, my published teaching materials explain that attributes should not be subjective and the levels of the attributes should not be ambiguous:

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[116] Greg M. Allenby, Jeff D. Brazell, John R. Howell, and Peter E. Rossi, "Economic Valuation of Product Features," *Quantitative Marketing and Economics*, Vol. 12, No. 4, 2014, pp. 421-456 at 433; Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014, p. 3.

Similarly, general survey research guides also recommend using "wording that is specific and concrete (as opposed to general and abstract." Jon A. Krosnick and Stanley Presser, "Question and Questionnaire Design," Bingley, UK, Emerald Group Publishing Limited, 2010" in Handbook of Survey Research, edited by Wright, James D., and Peter V. Marsden. (2010): 263-313 at 264.

[117] Weir Declaration, Exhibit 3, ¶ 35.

[118] Bryan K. Orme, "Formulating Attributes and Levels in Conjoint Analysis," *Sawtooth Software Research Paper Series*, 2002, p. 1.

[119] Bryan K. Orme, "Formulating Attributes and Levels in Conjoint Analysis," *Sawtooth Software Research Paper Series*, 2002, p. 1.

[120] Bryan K. Orme, "Formulating Attributes and Levels in Conjoint Analysis," *Sawtooth Software Research Paper Series*, 2002, p. 1.

> Subjective attributes such as "style" or "aesthetic appeal" as well as subjective levels such as "good," "modern," or levels that are defined as ranges (e.g., "$6 to $8"), should be avoided… The more room is left for interpretation by using subjective and ambiguous attributes and/or levels, the more likely it is that the responses expressed by consumers do not match the true preferences you are trying to measure.[121]

66. However, Mr. Weir has not provided details on the levels of most of the attributes that will be included in his proposed survey. Mr. Weir also does not indicate how he would determine the specific levels of the attributes, or how many levels to use for each attribute.[122] As Mr. Weir has failed to establish the levels of attributes he would include, or the method that he would use to determine those levels, he has failed to demonstrate the reliability of his proposed survey.

67. For price, Mr. Weir states that he will "conduct research of actual retail sales and market data and included [sic] these real world price points in the survey."[123] However, Mr. Weir does not describe how he will determine the number of price points used, or the range that the price points used will span, or how these determinations will incorporate "real world price points."

68. There are two attributes for which Mr. Weir has provided information on the levels: the Safety Warning and brand. As I discuss in Section V, Mr. Weir has proposed wording for his

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[121] Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014, p. 2.

[122] The Weir Declaration suggests that each attribute in Mr. Weir's proposed survey would have at most six levels. Weir Declaration, Exhibit 3, ¶ 33 (performing a calculation intended to determine the required sample size assuming that the largest number of levels for any attribute will be six). It is not clear how Mr. Weir decided that the largest number of levels for any one attribute will be six, or which attribute(s) this will apply to. Mr. Weir has provided no further information on the number of levels he will use for most of his attributes.

It is recommend that all attributes have a similar number of levels (e.g., between two to four levels, or between three to five levels) because if some attributes have many more levels than others, the estimated importance of the attributes with more levels tends to be overestimated. Elie Ofek and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014, p. 3.

[123] Weir Declaration, Exhibit 3, ¶ 53.

Safety Warning attribute, though he has not provided sufficient information to evaluate his basis for that wording.

69. The Weir Declaration indicates that brand would be included in Mr. Weir's proposed survey as a text field, and lists the brands to be included.[124] However, Mr. Weir has not explained how he determined to include these brands in a way that would allow evaluation of his basis for this decision.[125] Mr. Weir has testified that his attribute descriptions would be all text.[126] In other deposition testimony, though, Mr. Weir stated that he "might consider using the logos of the brand names rather than text for the brand names."[127]

C. Mr. Weir Does Not Provide Specifics About How He Will Pretest His Proposed Survey

70. The Weir Declaration states that Mr. Weir will "pretest" his proposed survey with approximately 50 respondents:

> Prior to putting the survey into the field, the conjoint questionnaire will be pretested with approximately 50 respondents. Following administration of the survey, respondents will be debriefed about the survey experience and questionnaire. I will conduct the pretest for quality control and quality assurance testing of the survey design; to validate that the survey questionnaire was programmed

[124] The Weir Declaration lists the following brands to be included in Mr. Weir's proposed survey: Fisher-Price, Ingenuity, Disney, Graco, and Halo. Weir Declaration, Exhibit 3, ¶ 27.

[125] In his deposition, Mr. Weir testified that he determined these brands from "Fisher-Price's own market research." Weir Deposition, 283:14-22. However, Mr. Weir has not explained what "market research" by Fisher-Price he is referring to or how he determined these brands using that research.

As I explain in my published teaching materials, to ensure that a conjoint survey's results be representative of the target market, the products in the study must be "representative of the products potentially available or that would be in the consideration set of the target market." Elie Ofek and Olivier Toubia, "Conjoint Analysis: Online Tutorial," *Harvard Business School Tutorial*, April 2014, p. 22. Mr. Weir has not provided any evidence that the brands that he proposes to include are representative of the products in the consideration set for Rock 'n Play Sleeper purchasers.

[126] Weir Deposition, 284:18-285:3, 288:4-16.

[127] Weir Deposition, 282:2-24 (Mr. Weir does not provide any explanation of how he would make this decision, other than that it "may be informed by the exploratory research").

> correctly to my specifications; to identify any survey questions that were unclear to respondents; and to analyze the data collection to identify any problems, such as unexpected missing response data or interview terminations.
>
> Additionally, I would test for demand artifacts, asking respondents about their beliefs about the sponsor and purpose of the survey.[128]

71. Mr. Weir does not provide any specifics about how he would conduct this pretest. As a result, Mr. Weir has not provided sufficient information for me to evaluate how his "pretest" would impact the reliability of his final survey.

72. For example, Mr. Weir states that as part of his pretest of his proposed survey he will "test for demand artifacts, asking respondents about their beliefs about the sponsor and purpose of the survey."[129] However, Mr. Weir does not explain how he will identify individuals who have been influenced by demand artifacts or how he would use his findings to alter the final survey.[130] The academic literature recognizes that it is not necessarily accurate to assume that demand artifacts exist for (or only for) subjects who "appear to have guessed the experimental hypothesis."[131] In addition, Mr. Weir does not explain how he would solicit feedback about "questions that were unclear to respondents"[132] or how he would use this feedback to alter the final survey.

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[128] Weir Declaration, Exhibit 3, ¶¶ 31-32.

[129] Weir Declaration, Exhibit 3, ¶ 32.

[130] An early paper on demand artifacts, Sawyer (1975), defines demand artifacts as including "all aspects of the experiment which cause the subject to perceive, interpret, and act upon what he believes is expected or desired of him by the experimenter" and further states that they "pose important threats" to a study's validity. Alan G. Sawyer, "Demand Artifacts in Laboratory Experiments in Consumer Research," *Journal of Consumer Research*, Vol. 1, No. 4, 1975, pp. 20-30 at 20.

[131] Terence A. Shimp, Eva M. Hyatt, and David J. Snyder, "A Critical Appraisal of Demand Artifacts in Consumer Research," *Journal of Consumer Research*, Vol. 18, No. 3, 1991, pp. 273-283 at 273.

[132] Weir Declaration, Exhibit 3, ¶ 31.

D. Mr. Weir Does Not Sufficiently Explain the Population That He Is Trying to Target, or Why His Target Population Is Reasonable

1. *Mr. Weir's Declaration Is Ambiguous About Whether He Will Survey Only Purchasers of the Rock 'n Play Sleeper, or Owners As Well, and Does Not Provide the Basis for His Decision*

73. As explained in the Reference Guide on Survey Research,

> One of the first steps in designing a survey or in deciding whether an existing survey is relevant is to identify the target population (or universe). The target population consists of all elements (i.e., individuals or other units) whose characteristics or perceptions the survey is intended to represent. … Identification of the proper target population or universe is recognized uniformly as a key element in the development of a survey… The definition of the relevant population is crucial because there may be systematic differences in the responses of members of the population and nonmembers. For example, consumers who are prospective purchasers may know more about the product category than consumers who are not considering making a purchase.[133]

74. The Weir Declaration has not clearly defined a target population for Mr. Weir's proposed survey. In particular, the Weir Declaration provides contradictory rules for who Mr. Weir plans to include in his proposed survey: only purchasers or both purchasers and users (which would include owners who used the product but did not purchase it).

75. In one place, the Weir Declaration states that respondents will be required to have purchased or used at least one Rock 'n Play product: "The sample will be drawn from the general population of the U.S. who had purchased or used at least one Rock 'n Play Product."[134] However, in another place, the Weir Declaration states that respondents will be required to have purchased a Rock 'n Play Sleeper product in the previous 36 months:

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[133] Shari Seidman Diamond, "Reference Guide on Survey Research," *Reference Manual on Scientific Evidence*, 2011, pp. 359-423 at 376-377 and FN 76.

[134] Weir Declaration, Exhibit 3, ¶ 34.

> Respondents will be asked if they have purchased one or more baby products in the past 36 months.
>
> o Those that have made such a purchase are then asked to select the types of products that they have purchased.
>
> o Those that indicate a purchase of a sleeper are then asked to identify the brand(s) of sleeper that they purchased. Those that indicate a Rock 'n Play will continue through the survey.[135]

76. Because of these inconsistencies, it is not clear whether Mr. Weir is targeting purchasers or both purchasers and users.[136]

2. *Mr. Weir's Proposed Survey Is Not Informative about the Purchase of a Used Rock 'n Play Sleeper*

77. Mr. Weir's declaration states that his proposed survey's "instructions inform respondents that they should imagine that they are going to purchase a new sleeper."[137] Mr. Weir's proposed survey is therefore not directly applicable to the decision to purchase a used Rock 'n Play Sleeper. I describe in Section II.D that Plaintiffs seek to certify several putative statewide classes, all of which include purchasers of Rock 'n Play Sleepers, regardless of whether they purchased new or used.

78. As I discuss above, it is not clear if Mr. Weir intends to survey purchasers or both purchasers and users. Regardless, Mr. Weir does not appear to limit his survey to respondents who obtained *new* Rock 'n Play Sleepers (as opposed to used).[138] Respondents who obtained their Rock 'n Play Sleepers while new might have different preferences than respondents who

[135] Weir Declaration, Exhibit 3, ¶ 21.

[136] In his deposition, Mr. Weir testified that both purchasers and recipients of the Rock 'n Play Sleeper are part of the putative class. Weir Deposition, 143:18-23.

[137] Weir Declaration, Exhibit 3, ¶ 23.

[138] Weir Declaration, Exhibit 3, ¶ 21.

obtained their Rock 'n Play Sleepers while used. Mr. Weir does not explain why it is reasonable to survey purchasers (or purchasers and users) who obtained used Rock 'n Play Sleepers about the decision to purchase a new Rock 'n Play Sleeper.

3. *Mr. Weir Does Not Plan to Evaluate Respondent Awareness of the Recall or this Litigation*

79. Mr. Weir does not plan to ask respondents if they are aware of either the recall of the Rock 'n Play Sleeper or this litigation.[139] Respondents who are aware of the recall and/or this litigation may have different preferences because of this knowledge that would lead them to respond differently to Mr. Weir's proposed survey. In particular, knowledge of the recall and/or litigation might inflate the importance of and the valuations for Mr. Weir's proposed safety disclaimer.[140]

80. At the time of the original retail purchase of new Rock 'n Play Sleepers, neither the recall nor this litigation had yet occurred. Therefore, to the extent that respondents who acquired the Rock 'n Play Sleeper by purchasing new at retail now have different preferences because of their awareness of the recall/litigation than they would have had at the time of purchase, their responses would be an unreliable measure of their original preferences.

81. At a minimum, Mr. Weir should ask about respondents' awareness of the recall and/or this litigation and should run an analysis to see if the respondents who are aware have different

[139] Mr. Weir's declaration indicates that he will test for demand artifacts by "asking respondents about their beliefs about the sponsor and purpose of the survey." Weir Declaration, Exhibit 3, ¶ 32. This inquiry is not equivalent to asking respondents if they are aware of the recall and/or this litigation. I discuss the incompleteness and potential inadequacy of Mr. Weir's description of how he will test for "demand artifacts" in Section VII.C.

[140] As I discuss in Section VII.D, Mr. Weir is unclear about his target population, but it includes individuals who purchased Rock 'n Play Sleeper and possibly also individuals who owned a Rock 'n Play Sleeper (but did not purchase it).

willingness to pay than other respondents. If these individual who are aware have substantially different willingness to pay than other respondents, they should be excluded from Mr. Weir's overall willingness to pay estimate. Mr. Weir does not provide any indication that he has considered these issues or has a plan to address them.

E. Mr. Weir Does Not Adequately Address the Sample Size of His Proposed Survey

82. Mr. Weir provides what he describes as a "rule of thumb" for the conjoint survey sample size: $\mathbf{n}\times\mathbf{t}\times\mathbf{a} \div \mathbf{c} \geq 500$, where **n** is the sample size, **t** is the number of choice tasks for each respondent, **a** is the number of options for each choice task (not including the option to purchase nothing), and **c** is the maximum number of attributes.[141] In support of this rule of thumb, Mr. Weir cites to a Sawtooth Software technical paper authored by Bryan Orme, which attributes this formula to Richard M. Johnson, who is the author of Sawtooth Software's choice-based conjoint system.[142] However, the paper cited by Mr. Weir is actually critical of use of this rule of thumb and suggests larger sample sizes, stating:

> Over the years, we have become concerned that practitioners use Johnson's rule-of-thumb to justify sample sizes that are too small. Some feel that they will have ample stability in estimates when each main-effect level of interest is represented across the design about 500 times. But 500 was intended to be a minimum threshold when researchers cannot afford to do better. It would be better, when possible, to have 1,000 or more representations per main-effect level.[143]

[141] Weir Declaration, Exhibit 3, ¶ 33.

[142] Bryan K. Orme, *Getting Started with Conjoint Analysis* Third Ed., Research Publishers LLC, 2014, pp. 68–69.

[143] Bryan K. Orme, *Getting Started with Conjoint Analysis* Third Ed., Research Publishers LLC, 2014, p. 69.

83. Mr. Weir's rule of thumb leads to sample sizes that are too low. This error can be demonstrated by means of Mr. Weir's opinion that even a sample size of 300 is "well in excess of the minimum recommended amount" from his rule of thumb. Specifically, Mr. Weir states:

> For this survey, I would likely sample approximately n=300 respondents; respondents would answer t=12 randomized choice tasks of a=3 alternatives per task; and the highest number of levels is c=6 analysis cells. The formula in this instance evaluates to 1,800; well in excess of the minimum recommended amount.[144]

84. Given Mr. Weir's description of his proposed survey, his chosen rule of thumb would require a minimum sample size of 500 × **c** ÷ (**t**×**a**), rounded up = 84 respondents. Mr. Weir provides no explanation of why such a low sample size would be adequate.

85. In addition, Mr. Weir states that "[t]ypically conjoint surveys collect data from at least 300 respondents if the goal of the research is to conduct robust quantitative research."[145] But Mr. Weir then proposes to use approximately 300 respondents, at the lowest end of what he states is typical for conducting "robust quantitative research," without providing any explanation (other than his incorrect "rule of thumb") for why only 300 respondents would be appropriate.

Executed this 16th day of June, 2021.

Olivier Toubia, PhD

[144] Weir Declaration, Exhibit 3, ¶ 33.

[145] Weir Declaration, Exhibit 3, ¶ 33.

Confidential

Exhibit 1
Summary of Named Plaintiffs Whose Depositions I Have Received

Row	Name	State of Residence	Products Purchased or Received	New or Used?	Used for Non-Sleep?	Used for Sleep?
Named Plaintiffs Who Purchased a Rock 'n Play Sleeper for Self and/or Received as a Gift						
1	Cassandra Mulvey	New York	Received as gift	New	Yes	Yes
2	Daniel Pasternacki	Colorado	Purchased (2 RNPSs)	New	Yes	Yes
3	Elizabeth Alfaro	New York	Purchased	New	No	Yes
4	Emily Barton	Arizona	Purchased	New	Yes	Yes
5	Emily Simmonds	New York	1st received as gift 2nd purchased	Used	Yes	Yes
6	Jena Huey	Florida	1st received as gift 2nd purchased 3rd purchased as gift	New	Yes	Yes
7	Jessie Poppe	New York	Received as gift	New	Yes	Yes
8	Joshua Nadel	New Jersey	1st received as gift 2nd purchased	New	Yes	Yes
9	Josie Willis	Tennessee	Purchased	New	Yes	Yes
10	Katharine Shaffer	Washington	Purchased	New	Yes	Yes
11	Kerry Mandley	Virginia	Received as gift	New	No	Yes
12	Linda Black	Texas	Purchased (not RNPS)[A]	New	Yes	Yes
13	Luke Cuddy	Massachusetts	Received as gift	New	Yes	Yes
14	Megan Fieker	Oklahoma	Received as gift (2 RNPSs)	New	Yes	Yes
15	Megan Kaden	California	Purchased (2 RNPSs)	One new one used	Yes	Yes
16	Melanie Nowlin	Arkansas	Purchased	New	Yes	Yes
17	Nancy Hanson	Iowa	Purchased (2 RNPSs)	One new one used	Yes	Yes
18	Renee Wray	Colorado	Received as gift	Used	Yes	Yes
19	Samantha Jacoby	New Jersey	Received as gift	New	Yes	Yes
Other Named Plaintiffs Who Purchased a Rock 'n Play Sleeper as a Gift						
20	Karen Flores	California	Purchased as gift	New	Doesn't know	Doesn't know
21	Rebecca Drover	Pennsylvania	Purchased as gift	New	Yes	Doesn't know

Note:
[A] Named Plaintiff Linda Black did not purchase a Rock 'n Play Sleeper, but rather a pink Mickey Mouse inclined sleeper from another brand. I include her in this table because her testimony provides useful information on how consumers use similar products to the Rock 'n Play Sleeper. Deposition of Linda Black, March 23, 2021, 74:1-75:23, 82:18-84:18, 194:16-196:17.

Sources for Corresponding Row Numbers:

[1] Deposition of Cassandra Mulvey, March 30, 2021, 24:2-5, 51:11-12, 51:16-21, 65:9-14, 66:2-6.

[2] Deposition of Daniel Pasternacki, April 6, 2021, 23:15-18, 48:22-24, 51:16-19, 52:14-19, 70:24-71:18, 75:18-76:2.

Exhibit 1
Summary of Named Plaintiffs Whose Depositions I Have Received

[3] Deposition of Elizabeth Alfaro, April 6, 2021, 10:5-7, 81:2-15, 147:4-6, 148:2-5, 162:9-11, 167:7-22.

[4] Deposition of Emily Barton, April 13, 2021, 50:19-21, 213:14-16, 228:1-19, 235:21-236:25, 259:13-23.

[5] Deposition of Emily Simmonds, April 13, 2021, 16:8-10, 54:23-55:3, 85:4-17, 101:1-5.

[6] Deposition of Jena Huey, April 16, 2021, 8:10-12, 127:23-128:20, 147:3-11, 154:4-18, 156:15-157:1, 175:2-7, 176:11-177:18.

[7] Deposition of Jessie Poppe, March 23, 2021, 22:5-6, 62:17-20, 175:8-13, 202:19-20, 207:11-15.

[8] Deposition of Joshua Nadel, April 13, 2021, 9:5-7, 84:20-85:7, 146:25-147:16, 158:20-159:20, 169:11-173:15.

[9] Deposition of Josie Willis, March 18, 2021, 26:11-12, 106:8-10, 106:18-19, 118:9-14, 142:25-143:8.

[10] Deposition of Katharine Shaffer, March 25, 2021, 25:10-12, 48:20-49:8, 100:17-20, 103:2-10.

[11] Deposition of Kerry Mandley, March 30, 2021, 42:4-6, 79:18-19, 129:1-5, 145:7-9, 160:1-10, 177:21-23, 179:10-15.

[12] Deposition of Linda Black, March 23, 2021, 45:4-7, 70:21-71:2, 139:14-21.

[13] Deposition of Luke Cuddy, March 23, 2021, 9:11-13, 85:23-86:1, 141:4-7, 172:4-7, 183:4-6.

[14] Deposition of Megan Fieker, March 25, 2021, 43:16-19, 188:10-16, 195:18-196:1, 210:24-211:2, 237:13-17, 239:17-240:7, 248:22-25, 249:6-13.

[15] Deposition of Megan Kaden, April 14, 2021, 14:18-19, 65:14-19, 66:5-17, 92:1-6, 93:2-8; Deposition of Megan Kaden, April 15, 2021, 132:24-134:25, 155:1-156:8.

[16] Deposition of Melanie Nowlin, April 1, 2021, 22:10-13, 141:2-20, 158:4-12, 188:18-22.

[17] Deposition of Nancy Hanson, March 25, 2021, 34:25-35:1, 103:7-19, 137:10-13, 139:4-12.

[18] Deposition of Renee Wray, May 26, 2021, 41:14-17, 102:15-103:22, 104:17-19, 157:13-15, 160:2-5, 172:4-7.

[19] Deposition of Samantha Jacoby, April 8, 2021, 25:23-26:5, 57:10-58:13, 60:19-61:11, 72:1-11.

[20] Deposition of Karen Flores, April 2, 2021, 26:1-7, 37:9-23, 49:19-21.

[21] Deposition of Rebecca Drover, April 8, 2021, 11:7-9, 60:1-8, 61:2-5, 75:2-24, 76:2-11, 76:17-20, 77:8-18.

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EMPLOYMENT

2012-present: Glaubinger Professor of Business, Columbia Business School, New York, NY.

2011-2012: Professor of Marketing, Columbia Business School.

2010-2011: Associate Professor of Marketing (with Tenure), Columbia Business School.

2007-2010: David W. Zalaznick Associate Professor of Business (without Tenure), Columbia Business School.

2004-2007: Assistant professor of marketing, Columbia Business School, New York, NY.

EDUCATION

Ph.D., Marketing, June 2004
Massachusetts Institute of Technology, Sloan School of Management, Cambridge, MA.

S.M., Operations Research, January 2001
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Ingénieur, June 2000
Ecole Centrale Paris, Paris, France.

RESEARCH INTERESTS

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HONORS AND AWARDS

Finalist for the Exeter Prize for Research in Experimental Economics, Decision Theory and Behavioral Economics, 2020.

Recipient of the John Little award for best marketing paper published in *Marketing Science* or *Management Science*, 2003, 2006, 2017, 2018.

Recipient of the INFORMS Society for Marketing Science Long Term Impact Award, 2016.

Recipient of the Paul E. Green award for the *Journal of Marketing Research* paper having the greatest potential for significant impact for marketing practice, 2015.

Recipient of the Don Lehmann award (best dissertation-based paper published in the *Journal of Marketing Research* or the *Journal of Marketing*), 2012.

Recipient of the Frank M. Bass outstanding dissertation award, 2005.

Recipient of the John A. Howard AMA dissertation award, 2005.

Finalist for the John Little award for best marketing paper published in *Marketing Science* or *Management Science*, 2013.

Finalist for the Paul Green Award, 2004, 2010.

Finalist for the INFORMS Society for Marketing Science Long Term Impact Award, 2011, 2012, 2013, 2014, 2015.

Finalist for the William F. O'Dell Award, 2015.

Haring Symposium Distinguished Scholar, 2013.

Management Science Meritorious Service Award, 2010.

MSI Young Scholar, 2007.

Presidential Fellow, Massachusetts Institute of Technology, 2001-2004.

Recipient of the Jean Walter Zellidja Fellowship (Académie Française), 1999.

Recipient of the Jean Gaillard Memorial Fellowship, 1999.

PROFESSIONAL ACTIVITY

2019-present: Chair of Marketing Division, Columbia Business School.

2019-present: Senior Editor, *Marketing Science*.

2019-present: member of the Tenure Review Advisory Committee (TRAC), Columbia University.

2016-2019: Faculty Director, The Eugene Lang Center for Entrepreneurship, Columbia Business School.

2016-2018: VP Education, INFORMS Society for Marketing Science.

2018: Co-Editor, *Quantitative Marketing and Economics*.

2013-2018: Senior Editor, *Customer Needs and Solutions*.

2013-2015: Associate Editor, *International Journal of Research in Marketing*.

2015-2017: Associate Editor, *Journal of Consumer Research*.

2014-2018: Associate Editor, *Management Science*.

2016-2018: Associate Editor, *Marketing Science*.

2010-2017: Associate Editor, *Operations Research*.

2008-2018: Member of the Editorial Board, *International Journal of Research in Marketing*.

2010-2018: Member of the Editorial Board, *Journal of Marketing Research*.

2006-present: Member of the Editorial Board, *Marketing Science*.

Ad-hoc reviewer: *American Economic Review, Applied Stochastic Models in Business and Industry, California Management Review, Decision Support Systems, European Journal of Operations Research, European Research Council, Interfaces, International Journal of Product Development, Israeli Science Foundation, Journal of Behavioral Decision Making, Journal of Business and Economic Statistics*, *Machine Learning, Marketing Letters*, *National Science Foundation*, *Physica A*, *Proceedings of the National Academy of Science*, *Product and Operation Management*, *Psychometrika, Review of Marketing Science*.

2011-present: Member of the Scientific Committee, *Recherche et Applications en Marketing*.

JOURNAL PUBLICATIONS

Toubia, Olivier, Duncan I. Simester, John R. Hauser, and Ely Dahan (2003), "Fast Polyhedral Adaptive Conjoint Estimation," *Marketing Science*, 22(3) (lead article).
  Winner, 2003 John Little award for best marketing paper published in *Marketing Science* or *Management Science.*
  Winner, 2005 Frank M. Bass outstanding dissertation award.
  Finalist, 2011 INFORMS Society for Marketing Science Long Term Impact Award.
  Finalist, 2012 INFORMS Society for Marketing Science Long Term Impact Award.

Finalist, 2013 INFORMS Society for Marketing Science Long Term Impact Award.

Toubia, Olivier, John R. Hauser, and Duncan I. Simester (2004), “Polyhedral Methods for Adaptive Choice-Based Conjoint Analysis,” *Journal of Marketing Research*, 16, 116-131.
Finalist, Paul Green award (best paper published in the *Journal of Marketing Research*).

Hauser, John R., and Olivier Toubia (2005), “The Impact of Utility Balance and Endogeneity in Conjoint Analysis,” *Marketing Science*, 24(3) (authors listed alphabetically).

Toubia, Olivier (2006), “Idea Generation, Creativity, and Incentives,” *Marketing Science*, 25(5) (lead article).
Winner, 2006 John Little award for best marketing paper published in *Marketing Science* or *Management Science.*
Finalist, 2013 INFORMS Society for Marketing Science Long Term Impact Award.
Finalist, 2014 INFORMS Society for Marketing Science Long Term Impact Award.
Finalist, 2015 INFORMS Society for Marketing Science Long Term Impact Award.
Winner, 2016 INFORMS Society for Marketing Science Long Term Impact Award.

Toubia, Olivier, and Laurent Florès (2007), “Adaptive Idea Screening Using Consumers,” *Marketing Science*, 26(3), 342-361.

Toubia, Olivier, John R. Hauser, and Rosanna Garcia (2007), “Probabilistic Polyhedral Methods for Adaptive Choice-Based Conjoint Analysis: Theory and Application,” *Marketing Science*, 26(5) (lead article).
Winner, 2005 John A. Howard AMA dissertation award.

Toubia, Olivier, and John R. Hauser (2007), “On Managerial Efficiency for Experimental Designs,” *Marketing Science*, 26(6).

Evgeniou, Theodoros, Massimilano Pontil, and Olivier Toubia (2007), "A Convex Optimization Approach to Modeling Consumer Heterogeneity in Conjoint Estimation," *Marketing Science*, 26(6) (authors listed alphabetically).

Abernethy, Jacob, Theodoros Evgeniou, Olivier Toubia, and Jean-Philippe Vert (2008), "Eliciting Consumer Preferences using Robust Adaptive Choice Questionnaires," *IEEE Transactions on Knowledge and Data Engineering*, 20(2) (lead article - authors listed alphabetically).

Netzer, Oded, Olivier Toubia, Eric T. Bradlow, Ely Dahan, Theodoros Evgeniou, Fred M. Feinberg, Eleanor M. Feit, Sam K. Hui, Joseph Johnson, John C. Liechty, James B. Orlin, Vithala R. Rao (2008),“Beyond Conjoint Analysis: Advances in Preference Measurement,” *Marketing Letters*, 19(3).

Jarnebrant, Peter, Olivier Toubia, and Eric Johnson (2009), "The Silver Lining Effect: Formal Analysis and Experiments," *Management Science*, 55(11).

Stephen, Andrew, and Olivier Toubia (2009), "Explaining the Power-Law Degree Distribution in a Social Commerce Network," *Social Networks*, 31 (262-270).

Ofek, Elie, and Olivier Toubia (2009), "Marketing and Innovation Management: An Integrated Perspective," *Foundations and Trends in Marketing*, 4(2), 77-128.

Stephen, Andrew, and Olivier Toubia (2010), "Deriving Value from Social Commerce Networks," *Journal of Marketing Research*, 47(2), 215-228.
Finalist, Paul Green award (best paper published in the *Journal of Marketing Research*).
Winner, Don Lehmann award (best dissertation-based paper published in the *Journal of Marketing Research* of the *Journal of Marketing*).
Finalist, 2015 William F. O'Dell Award.

Hauser, John, Olivier Toubia, Theodoros Evgeniou, Rene Befurt, and Daria Dzyabura (2010), "Disjunctions of Conjunctions, Cognitive Complexity, and Consideration Sets," *Journal of Marketing Research*, 47(3), 485-496.

Toubia, Olivier, Martijn G. de Jong, Daniel Stieger, and Johann Fueller (2012), "Measuring Consumer Preferences Using Conjoint Poker," *Marketing Science*, 31(1), 138-156.

Toubia, Olivier, Eric Johnson, Theodoros Evgeniou, and Philippe Delquié (2013), "Dynamic Experiments for Estimating Preferences: An Adaptive Method of Eliciting Time and Risk Parameters," *Management Science*, 59(3), 613-640.

Toubia, Olivier, and Andrew T. Stephen (2013), "Intrinsic versus Image-Related Utility in Social Media: Why Do People Contribute Content to Twitter?", *Marketing Science*, 32(3), 368-392 (lead article).
Finalist for the John Little award for best marketing paper published in *Marketing Science* or *Management Science*, 2013.

Toubia, Olivier, Jacob Goldenberg, and Rosanna Garcia (2014), "Improving Penetration Forecasts Using Social Interactions Data," *Management Science*, 60(12), 3049-3066.

Yang, Cathy L., Olivier Toubia, and Martijn G. de Jong (2015), "A Bounded Rationality Model of Information Search and Choice in Preference Measurement," *Journal of Marketing Research*, 52(2), 166-183.
Winner of the Paul E. Green award for the 2015 *Journal of Marketing Research* paper having the greatest potential for significant impact for marketing practice.

Lehmann, Donald R., Oded Netzer, and Olivier Toubia (2015), "The Future of Quantitative Marketing: Results of a Survey," *Customer Needs and Solutions*, 2, 5-18.

Luo, Lan, and Olivier Toubia (2015), "Improving Online Idea Generation Platforms and Customizing the Task Structure Based on Consumers' Domain Specific Knowledge," *Journal of Marketing*, 79(5), 100-114.

Pham, Michel Tuan, Ali Faraji-Rad, Olivier Toubia, and Leonard Lee (2015), "Affect as an ordinal system of utility assessment," *Organizational Behavior and Human Decision Processes*, 132 (November), 81-94.

Toubia, Olivier, and Oded Netzer (2017), "Idea Generation, Creativity, and Prototypicality," *Marketing Science*, 36(1), 1-20 (lead article).

Winner, 2017 John Little award for best marketing paper published in *Marketing Science* or *Management Science.*

Liu, Jia, and Olivier Toubia (2018), "A Semantic Approach for Estimating Consumer Content Preferences from Online Search Queries," *Marketing Science*, 37(6), 930-952.

Winner, 2018 John Little award for best marketing paper published in *Marketing Science* or *Management Science.*

Yang, Cathy L., Olivier Toubia, and Martijn G. de Jong (2018), "Attention, Information Processing and Choice in Incentive-Aligned Choice Experiments," *Journal of Marketing Research*, 55(6), 783-800 (lead article).

Johnson, Eric, Stephan Meier, and Olivier Toubia (2019), "What's the Catch? Suspicion in Motives of Banks and Sluggish Refinancing," *The Review of Financial Studies*, 32(2), 467-495.

Finalist, 2020 Exeter Prize for Research in Experimental Economics, Decision Theory and Behavioral Economics.

Toubia, Olivier, Garud Iyengar, Renée Bunnell, and Alain Lemaire (2019), "Extracting Features of Entertainment Products: A Guided LDA Approach Informed by the Psychology of Media Consumption," *Journal of Marketing Research*, 56(1), 18-36.

Liu, Jia, and Olivier Toubia (2020), "Search Query Formation by Strategic Consumers," *Quantitative Marketing and Economics*, 18, 155-194.

Toubia, Olivier (2020), "A Poisson Factorization Topic Model for the Study of Creative Documents (and their Summaries)," *Journal of Marketing Research* (forthcoming).

Liu, Jia, Olivier Toubia, and Shawndra Hill (2020), "Content-Based Model of Web Search Behavior: An Application to TV Show Search," *Management Science* (forthcoming).

Friedman, Elizabeth, and Olivier Toubia (2020), "Pricing Fairness in a Pandemic: Navigating Unintended Changes to Value or Cost," *Journal of the Association for Consumer Research* (special issue on COVID-19), forthcoming.

Toubia, Olivier, Jonah Berger, and Jehoshua Eliashberg (2021), “How Quantifying the Shape of Stories Predicts Their Success," *Proceedings of the National Academy of Sciences* (forthcoming).

BOOK CHAPTERS

Toubia, Olivier, Theodoros Evgeniou, and John R. Hauser (2008), “Optimization-Based and Machine-Learning Methods for Conjoint Analysis: Estimation and Question Design,” in *Conjoint Measurement: Methods and Applications, 4th edition*, edited by A. Gustafsson, A. Herrmann, and F. Huber.

Toubia, Olivier (2010), “New Product Development,” in *Handbook of Technology Management* (edited by Hossein Bidgoli).

Toubia, Olivier (2018), “Conjoint Analysis,” in *Handbook of Marketing Analytics: Methods and Applications in Marketing Management, Public Policy, and Litigation Support* (edited by Natalie Mizik and Dominique M. Hanssens).

OUTSIDE ACTIVITIES

Columbia Business School requires faculty members to disclose any recent activities that might present a real or apparent conflict of interest. Recently I have:

-Done litigation consulting work related to one consumer packaged good companies, three technology companies, two automotive companies, two health supplement companies, one toy company.

-Developed a case/learning module with a colleague in a peer institution.

Olivier Toubia, Ph.D.
Glaubinger Professor of Business
Columbia Business School

June 2021

Testimony in the Past Four Years

Anthony Shamrell et al. v. Apple Inc., Superior Court of the State of California County of San Diego, Case No: 37-2013-00055830-CU-PL-CTL. Deposed, May 2019.

Justin Lytle and Christine Musthaler et al. v. Nutramax Laboratories, Inc., Central District of California, Case No.: 5:19-cv-00835-JBG-SP. Deposed, May 2021.

Appendix C

Materials Relied Upon

Legal Documents

Consolidated Amended Complaint, *In Re: Rock 'n Play Sleeper Marketing, Sales Practices, and Products Liability Litigation*, 1:19-md-2903, October 28, 2019.

Memorandum of Law in Support of Plaintiffs' Motion for Class Certification, *In Re: Fisher-Price Rock 'n Play Sleeper Marketing, Sales Practices, and Products Liability Litigation*, 1:19-md-2903, February 8, 2021.

Transcript of Status Conference, *In re: Rock 'n Play Sleeper Marketing, Sales Practices, and Products Liability Litigation*, Case No. 1:19-md-2903.

Expert Reports and Declarations

Declaration of Colin B. Weir, February 8, 2021.

Declaration of J. Michael Dennis, *McMorrow, et al. v. Mondelez International, Inc.*, 3:17-cv-02327-BAS-JLB, May 4, 2020.

Depositions

Deposition of Cassandra Mulvey, March 30, 2021.

Deposition of Colin B. Weir, March 11, 2021.

Deposition of Daniel Pasternacki, April 6, 2021.

Deposition of Elizabeth Alfaro, April 6, 2021.

Deposition of Emily Barton, April 13, 2021.

Deposition of Emily Simmonds, April 13, 2021.

Deposition of Jena Huey, April 16, 2021.

Deposition of Jessie Poppe, March 23, 2021.

Deposition of Joshua Nadel, April 13, 2021.

Deposition of Josie Willis, March 18, 2021.

Deposition of Karen Flores, April 2, 2021.

Deposition of Katharine Shaffer, March 25, 2021.

Deposition of Kerry Mandley, March 30, 2021.

Deposition of Linda Black, March 23, 2021.

Deposition of Luke Cuddy, March 23, 2021.

Deposition of Megan Fieker, March 25, 2021.

Deposition of Megan Kaden, April 14, 2021.

Deposition of Megan Kaden, April 15, 2021.

Deposition of Melanie Nowlin, April 1, 2021.

Deposition of Nancy Hanson, March 25, 2021.

Deposition of Rebecca Drover, April 8, 2021.

Deposition of Renee Wray, May 26, 2021.

Deposition of Samantha Jacoby, April 8, 2021.

Deposition of Sarah Ford, December 11, 2020.

Bates-Stamped Documents

FSHR0060073-FSHR0060084.

"Baby Gear Spring 2016," FSHR0059366-FSHR0059439.

"Voice of the Consumer Baby Gear," 2013, FSHR0059256-FSHR0059277.

Public Documents

Allen, Mark A., Robert E. Hall, and Victoria A. Lazear, "Reference Guide on Estimation of Economic Damages," *Reference Manual on Scientific Evidence*, 2011, pp. 425-502.

Allenby, Greg M., Jeff D. Brazell, John R. Howell, and Peter E. Rossi, "Economic Valuation of Product Features," *Quantitative Marketing and Economics*, Vol. 12, No. 4, 2014, pp. 421-456.

Allenby, Greg M., Jeff Brazell, John R. Howell, and Peter E. Rossi, "Valuation of Patented Product Features," *The Journal of Law & Economics*, Vol. 57, No. 3, August 2014, pp. 629-663.

Arrow, Kenneth, Robert Solow, Paul R. Portney, Edward E. Leamer, Roy Radner, and Howard Schuman, "Report of the NOAA Panel on Contingent Valuation," January 11, 1993.

Ben-Akiva, Moshe, Daniel McFadden, and Kenneth Train, "Foundations of Stated Preference Elicitation: Consumer Behavior and Choice-based Conjoint Analysis," *Foundations and Trends in Econometrics*, Vol. 10, No. 1-2, 2019, pp. 1-144.

Bradlow, Eric T., "Current Issues and a 'Wish List' for Conjoint Analysis," *Applied Stochastic Models in Business and Industry*, Vol. 21, No. 4-5, 2005, pp. 319-323.

Diamond, Shari Seidman, "Reference Guide on Survey Research," *Reference Manual on Scientific Evidence*, 2011, pp. 359-423.

Drewnowski, Adam, Howard Moskowitz, Michele Reisner, and Bert Krieger, "Testing consumer perception of nutrient content claims using conjoint analysis," *Public Health Nutrition*, Vol. 13(5), 2010, pp. 688-694.

Gadioli, Izabel, Livia Pineli, Juliana Rodrigues, Alinne Campos, Isadora Gerolim, and Marileusa Chiarello, "Evaluation of Packing Attributes of Orange Juice on Consumers' Intention to Purchase by Conjoint Analysis and Consumer Attitudes Expectation," *Journal of Sensory Studies*, Vol. 28, pp. 57-65.

Green, Paul E., Abba M. Krieger, and Yoram (Jerry) Wind, "Thirty Years of Conjoint Analysis: Reflections and Prospects," *Interfaces*, Vol. 31, No. 3, 2001, pp. S56-S73.

Haubl, Gerald, Benedict Dellaert, and Bas Donkers, "Tunnel Vision: Local Behavioral Influences on Consumer Decisions in Product Search," *Marketing Science*, Vol. 29, No. 3, September 22, 2009, pp. 438-455.

Hirogaki, Mitsunori, "Estimating Consumers' Willingness to Pay for Health Food Claims: A Conjoint Analysis," *International Journal of Innovation, Management and Technology*, Vol. 4, No. 6, 2013, pp. 541-546.

Krosnick, Jon A., and Stanley Presser, "Question and Questionnaire Design," Bingley, UK, Emerald Group Publishing Limited, 2010.

Ofek, Elie, and Olivier Toubia, "Conjoint Analysis: A Do it Yourself Guide," *Harvard Business School*, August 4, 2014.

Ofek, Elie, and Olivier Toubia, "Conjoint Analysis: Online Tutorial," *Harvard Business School Tutorial*, April 2014.

Orme, Bryan K., "Formulating Attributes and Levels in Conjoint Analysis," *Sawtooth Software Research Paper Series*, 2002.

Orme, Bryan K., *Getting Started with Conjoint Analysis* Third Ed., Research Publishers LLC, 2014.

Orme, Bryan K., and Keith Chrzan, "Becoming an Expert in Conjoint Analysis: Choice Modeling for Pros," 2017.

Rao, Vithala R., *Applied Conjoint Analysis*, Springer, 2014.

Rao, Vithala R., and Henrik Sattler, "Measurement of Price Effects with Conjoint Analysis: Separating Informational and Allocative Effects of Price," *Conjoint Measurement: Methods and Applications*, Berlin, Springer, 2007.

Sawyer, Alan G., "Demand Artifacts in Laboratory Experiments in Consumer Research," *Journal of Consumer Research*, Vol. 1, No. 4, 1975, pp. 20-30.

Schkade, David A., and Daniel Kahneman, "Does Living in California Make People Happy? A Focusing Illusion in Judgments of Life Satisfaction," *Psychological Science*, Vol. 9, No. 5, 1998, pp. 340-346.

Shimp, Terence A., Eva M. Hyatt, and David J. Snyder, "A Critical Appraisal of Demand Artifacts in Consumer Research," *Journal of Consumer Research*, Vol. 18, No. 3, 1991, pp. 273-283.

Toubia, Olivier, "Conjoint Analysis," *Handbook of Marketing Analytics*, Edward Elgar Publishing, 2018.

Tversky, Amos, and Daniel Kahneman, "Choices, Values, and Frames," *American Psychologist*, Vol. 39, No. 4, 1984, pp. 341-350.

Tversky, Amos, and Daniel Kahneman, "The Framing of Decisions and the Psychology of Choice," *Science*, Vol. 211, No. 4481, 1981, pp. 453-458.

"What is Conjoint Analysis?," *Sawtooth Software*, https://sawtoothsoftware.com/conjoint-analysis.

Conjoint Analysis Tutorial Overview

Welcome to the conjoint analysis tutorial, which provides an interactive tool to teach you about conjoint analysis. Successful completion of the material will prepare you for designing, collecting, and using conjoint analysis customer data in practice. This tutorial is part of a comprehensive toolkit on conjoint analysis that includes two additional components:

- A set of exercises to practice using conjoint analysis data, with the aid of a market choice predictor to make business decisions ('Marketing Simulation: Using Conjoint Analysis for Business Decisions', HBP Courseware #515-713 (https://cb.hbsp.harvard.edu/cbmp/product/515713-HTM-ENG)).
- A Do-It-Yourself (DIY) guide that provides a step-by-step explanation for how to construct, run and analyze a conjoint analysis study. The DIY guide also provides access to a customizable choice predictor, allowing you to use your own conjoint data for evaluating business decisions ('Conjoint Analysis: A Do-it-Yourself Guide', HBP Courseware: #515024 (https://cb.hbsp.harvard.edu/cbmp/product/515024-PDF-ENG)).

Using the Toolkit

Read through the tutorial below and try the interactive tasks that are designed to help you solidify your understanding of the main concepts.

What Who When and Why

In this module you will learn the basics of conjoint analysis, specifically: what conjoint anlaysis is, who tends to use it, and when and why it is applied.

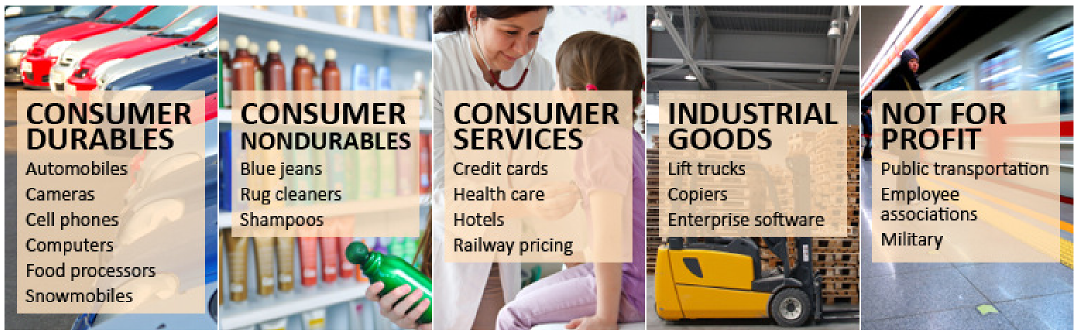
What is Conjoint Analysis?

Most decisions we make in the real world involve trade-offs. For instance, consumers make trade-offs when purchasing products: Should the premium car with all-wheel drive be purchased or should the economy car with better gas mileage be purchased? Companies must consider these consumer trade-offs when developing new products and services, allowing them to make better strategic decisions. For example: what features should be included in the product and which features left out in order to maximize profits? How should a new service with more advanced capabilities be priced to grow market share? To help managers understand how customers make trade-offs among various product or service characteristics, a method of market research called conjoint analysis has been developed.

Conjoint analysis allows researchers to quantify consumer preferences for various features and characteristics of products

or services. It essentially builds a mathematical model of consumer preferences, thus allowing managers to predict how consumers would choose between products and services that are or may become available on the market.

Conjoint analysis is used in a range of industries and for a number of strategic decisions such as: product design, product line optimization, pricing, segmentation, and market-share prediction.



Who Uses Conjoint and When?

Questions for which conjoint analysis is relevant to address include:

- Which features should we include in our products/services?
- How many different products/services should we offer?
- How much are consumers willing to pay for each feature of our product/service? How much would they be willing to pay extra for an improvement on an existing characteristic?
- How should we price our products/services?
- What market share should we expect to obtain if we launch product/service X?
- How do consumers differ in their preferences? Which segment(s) of consumers should we focus on serving? What product(s) would appeal to this (these) segment(s) relative to existing alternatives in the marketplace?

Why Use Conjoint?

One approach for collecting information on consumer preferences is to conduct interviews, focus groups, or other qualitative techniques. However, these approaches do not lend themselves to quantifying preferences and predicting how consumers would react to specific changes in product design and/or pricing; particularly when there are multiple competitors and alternatives to choose from in the marketplace.

Another approach is to directly ask consumers to specify their preferences for various features and characteristics of a product or service. However, consumers are usually unable to quantify how they would trade off one feature for another, and when asked, many state that "everything is important." Consequently, these approaches are fraught with problems and difficult to rely on for making business decisions.

Conjoint analysis provides a solution to these problems by having consumers evaluate products and services that are described as "bundles" of features and characteristics. Market researchers commonly refer to these characteristics as "attributes." This approach forces consumers participating in the study to consider these attributes jointly and to make tradeoffs between them, thereby providing a more accurate window into how consumers make decisions about products and services in real life. Just how conjoint analysis works and how managers use the results to make decisions will become clearer in this tutorial.

Key Terminology

In conjoint analysis, we assume that each level of each attribute has a certain utility for the consumer. The utility of each level of each attribute is called a partworth, because it captures how much this PART of the product is WORTH to the consumer. Then we assume that the utility of a hypothetical product, also called a profile, is the sum of the partworths of the attribute levels in the profile. The higher the utility of a profile, the more likely it is that a consumer will want to buy it and the higher the price he or she is willing to pay for it.

The following terms, which you can reference at any time, are commonly used in conjoint analysis and will become clearer as you advance through the tutorial:

Attributes
are features and characteristics that define various aspects of a product or service. For example, attributes for cars can include "brand origin," "body style," "engine type," "price," "number of seats," etc.

Levels
are the values that each attribute may take. For example, "brand origin" could be "American" "European" "Japanese"; "body style" could be "sedan" "sports car" "SUV"; "price" could be "$20,000" "$30,000" or "$40,000" etc.

Profiles
are hypothetical products or services described as bundles of attributes that are each set at a particular level. One example may be an American car with a sedan body type and gasoline engine priced at $20,000.

Appendix D

EXAMPLE OF A CAR PROFILE:
AMERICAN
SEDAN
GASOLINE ENGINE
$20,000

Try It 1 | Try It 2

Think about a credit card and drag each of the associated terms to its correct category.

1 mile earned per $ spent

Number of miles earned per $ spent

No yearly fee, no cash back, 1 mile earned per $ spent, 12% APR

Attribute

drag term here

Level

drag term here

Profile

drag term here

Check My Answers

Utility
is a measure of the value provided to a consumer. For example, the utility of a specific profile is the overall value that the bundle of attributes in the profile provides the consumer.

Partworths
are the utility of each attribute level. They are called partworths because they capture how much each PART of the product is WORTH to the consumer. Therefore, the utility of a profile is the sum of the partworths of the attribute levels in the profile.

Utils
are the unit that partworths are measured in. Utils reflect a relative preference for an attribute level compared to other attribute levels in the study. The total utility of a profile is obtained by adding the utils for each partworth together.

Baseline levels
are partworths arbitrarily set to a value of 0 utils. One level of each attribute is selected as a baseline. For example, in a rating-based conjoint study, such as the one used in this tutorial, we set the "Japanese," "Sedan," "$20,000," and "Gasoline" levels to 0 utils. Therefore, the partworths of the other levels are then relative to the baseline level. So, a consumer's partworth for the "American" or "European" level indicates a relative preference compared to the baseline. A positive partworth for the "American" level, for instance, indicates a preference for American vehicles over Japanese vehicles. A negative partworth for the "European" level, as another example, indicates a preference for Japanese vehicles over European vehicles.

Try It 3 Try It 4

Given the partworths below, select one level from each attribute to configure the product profile that delivers the ***highest*** possible utility for the consumer.

Partworths for a Consumer

Baseline	Engine Type	Body Style	Brand Origin	Price	Total
Baseline **5.24**	Electric **0.70**	Sedan **0.00**	American **0.09**	$20,000 **0.00**	
	Gas **0.00**	Sports Car **0.08**	European **0.27**	$30,000 **-0.48**	
	Hybrid **1.91**	SUV **-0.41**	Japanese **0.00**	$40,000 **-1.05**	
5.24	Please select one level above	Please select one level above	Please select one level above	Please select one level above	**5.**

Check My Answer

In this section you will learn how a conjoint analysis study is conducted. You will be following a US car manufacturer, Top Motors Company (TM), as it begins to define the first in a new line of environmentally friendly cars. For example, TM management is wondering whether the new car should be a sedan, a sport utility vehicle (SUV), or a sports car and whether it should be all-electric or hybrid. They are also wondering how to price the various new product options their company might consider and what market share they would be able to capture with such a car.

Overview

TM wants to understand the preferences of potential customers for environmentally friendly cars and to assess what kind of market opportunity each car configuration would present. In particular, they seek to find out what premium (if any) consumers are willing to pay for environmentally friendly cars (as opposed to gasoline-powered cars) made in the United States (vs. in other countries) and which type of car (e.g., sedan, SUV, sports) generates the greatest opportunity for the company.

In this case, therefore, the company needs to uncover the utility for consumers of various possible cars that TM and its competitors may develop and launch. Let's take a look at the steps involved in creating a conjoint analysis study that can help TM uncover these preferences.

Step 1: Choose Attributes

TM's first step towards conducting an effective conjoint analysis is to specify the product attributes that are most relevant to be able to answer their questions. They begin by identifying the following four product attributes:

- Brand origin
- Body style
- Engine type
- Price (Manufacturer's Suggested Retail Price)

The utility of a car profile to the consumer will be the sum of the values that these individual attributes provide:

U(Car) = u(Brand Origin) + u(Body Style) + u(Engine Type) + u(Price)

Note the important ability of conjoint to handle a mix of hard, tangible features like engine type and body style and intangibles such as brand origin.

Using Qualitative Research Methods to Determine Product Attributes
TM is comfortable that the attributes they have selected to include in the study represent the most relevant factors in consumers' decisions in the context of evaluating environmentally friendly cars. Often though, a preliminary research stage is necessary to elicit possible relevant attributes from consumers. This is especially true if the firm has little experience in the category or if possible shifts in consumer tastes and needs may change the key attributes consumers care about. In practice, there are many attributes that make up a product or service. But the more attributes that are included in the study, the more complex the profile descriptions become and the more difficult it is for study participants to provide meaningful responses. It is therefore good practice to limit the number of attributes to the 4-6 that are likely to be important to consumers and that will be most informative to the company given the decisions it faces.

Step 2: Choose Relevant Levels for Attributes

Next, TM looks at each attribute and determines the relevant levels that the consumers should be asked to evaluate.

In this example, they specify the same number of levels (3) for each of the attributes. Conjoint can accommodate any practical number of levels for an attribute, although it is recommended that all attributes have approximately the same number of levels and to limit the number of levels to 4 or 5 so as not to overload participants in the study.

Attribute	Brand Origin	Body Style	Engine Type	Price
Levels	American European Japanese	 Sedan  SUV  Sports (coupe)	Gasoline Hybrid Electric	$20,000 $30,000 $40,000

Some attributes are categorical, meaning that they can take on only particular discrete levels (as is the case here with brand origin, body style, and engine type), while other attributes are continuous, meaning they can take on any

numerical value (as is the case with price). For purposes of the study, the company needs to choose specific levels for all attributes. For the categorical attributes, TM includes the discrete levels that they want to compare. For price, they select particular levels that cover the range of reasonable values (in $10,000 increments).

As we will see later, once the partworths are estimated, we can calculate the utility for any intermediate level of an attribute that is continuous through interpolation, so having to choose only a subset of levels does not limit making inferences about other levels in the range. It is possible to include visual information in the description if it can aid participants in understanding what each level means, such as the images of vehicles in the table above in the "Body Style" column. If attributes are new to the product category, detailed descriptions may need to be given to the respondents in the study. In the mid 1990s, for instance, there were no mass-produced hybrid vehicles on the market and consumer awareness of hybrid and electric engine technology was low. If an automobile manufacturer was designing a conjoint study evaluating the utility of a hybrid or electric engine compared to a traditional gasoline engine in the mid 1990s, then the survey would need to clearly illustrate or define the differences between the various engine technologies.

Step 3: Create Product Profiles

The next step is to construct product profiles that consumers will evaluate. It is important that these product profiles represent offerings that may be available on the market or that don't seem infeasible or unrealistic to offer.

Examples of Product Profiles

Profile #	Brand Origin	Body Type	Engine Type	Price
1	Japanese	Sedan	Gasoline	$20,000
2	European	SUV	Gasoline	$40,000
3	American	SUV	Electric	$30,000
4	European	Sports Car	Hybrid	$30,000
5	Japanese	Sports Car	Electric	$40,000

The number of attributes and levels chosen determines how many possible profiles can be constructed. To conceptualize profiles, attributes, and levels one can think of a prix fixe menu where you have a choice between 3 appetizers, 3 main courses, 3 deserts, and 3 drinks. Appetizers, main courses, deserts, and drinks are attributes. The 3 choices available for the appetizer, main course, desert, and drink are all levels. A specific order placed by a consumer, including 1 level from each attribute, is a profile. The total number of possible order combinations that a consumer can place is equal to:

3^4 = 81 possible profiles

A more generic way to determine the number of potential combinations that can be produced from a fixed number of attributes and levels can be defined as:

Maxium Number of Profiles = Number of Levels$_{\text{Attribute 1}}$ * Number of Levels$_{\text{Attribute 2}}$ * Number of Levels$_{\text{Attribute 3}}$ * ... * Number of Levels$_{\text{Attribute N}}$

Recall that TM has 4 attributes that each have 3 levels, so TM also has a maximum of 81 possible profiles. In many

situations, however, this number can be even higher than 81 (if more attributes or levels are included in the study). Because it is not practical to ask consumers to evaluate such high numbers of profiles, researchers will typically use a subset of all possible profiles. TM narrowed the possible profiles to be included in the study down to 15.

As previously mentioned, it is important to avoid situations where combinations of attribute levels result in unrealistic scenarios. For example, suppose "compact" was added as a level of the "body type" attribute and a new attribute, "number of seats," was added that included the level "seven seats." With these new attribute levels, many of the possible product profiles would be counterintuitive. Imagine that a car company built a vehicle with seven seats and then marketed the car as a "compact" vehicle. In this case, since a seven-seat compact vehicle is seemingly infeasible, the conjoint study should either drop the "compact" level or remove any level greater than "five seats."

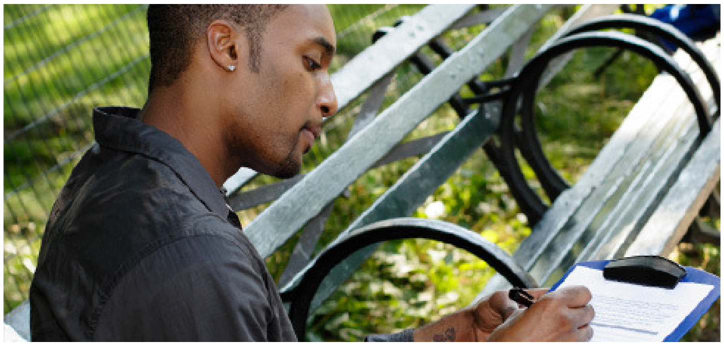
Selecting the Best Profiles

It is important to note that using any random set of profiles may lead to unusable data. The idea is to select profiles in which the attributes have enough variations to be able to quantify the link between attributes and preferences and capture important tradeoffs. The number of profiles should be large enough to allow for estimating all the partworths with some reliability but not too large in order to limit the burden imposed on respondents. There exist libraries and software that help select which profiles to show to consumers.

For more information on this topic refer to:

- Conjoint Analysis: A Do-it-Yourself Guide (514-097)
  Elie Ofek and Olivier Toubia
  Harvard Business School Publishing

Step 4: Poll Consumers



TM's next step is to obtain consumer data for its selected profiles. That is, have consumers evaluate these profiles in a way that would allow the market research team to infer each respondent's preferences for the various attributes.

There are several methods of polling consumers in a conjoint study. One popular format, choice-based conjoint, asks consumers to make a series of choices between two or more profiles that are simultaneously shown to them. Another popular format is ratings-based conjoint analysis. TM goes with the ratings-based approach and asks consumers to rate their preference for each of the 15 profiles it has chosen to include in the study.

For ratings-based conjoint analysis, researchers use a scale (often referred to as a Likert scale) to collect data on the respondents' strength of preference for each profile, as shown below:

Example of a Consumer's Profile Ratings

Profile #	Brand Origin	Body Type	Engine Type	Price	1	2	3	4	5	6	7
1	Japanese	Sedan	Gasoline	$20,000			X				
2	European	SUV	Gasoline	$40,000		X					
3	American	SUV	Electric	$30,000					X		
4	European	Sports Car	Hybrid	$30,000				X			
5	Japanese	Sports Car	Electric	$40,000						X	

Instructions for respondents could include the following:

"Assuming you are in the market for a new car, please rate how likely you would be to purchase each of the following options (1=not at all likely, 7=very likely)."

Or

"Please rate each of the following car options by selecting the number on the 7-point preference scale (1 = lowest, 7 = highest) that best reflects the strength of your preference."

One should also alert respondents that each car option in this study is described on a separate row.

Step 5: Generate Regression Report

Once responses are collected, TM managers are ready to start analyzing and interpreting the data. They use a simple statistical method called ***multiple linear regression***[1] to compute the partworths for each attribute level for each of the study's participants.

They first define a "baseline" profile. For example:

Japanese, sedan, gasoline, $20,000

The partworths of the levels present in the baseline profile are set to zero in the regression. The partworths of the other levels are then captured by the regression coefficients and are interpreted as deviations from the baseline. A positive partworth indicates a level that is preferred to the baseline level (e.g., someone who prefers an SUV over a sedan should have a positive partworth for SUV), and vice versa. Consider the example of one consumer, whose regression output is reported below. This person would rate a sports car 2.21 utils higher than a sedan with the same brand origin, engine type, and price; however, he or she would rate the same car 2.50 utils lower if it were an SUV instead of a sedan.

Sample Regression Report for a Particular Respondent

	Coefficients
Intercept	4.12
Japanese	0
American	0.60
European	1.16
Sedan	0

	Coefficients
SUV	-2.50
Sports Car	2.21
Gasoline	0
Hybrid	0.16
Electric	0.91
$20,000	0
$30,000	-1.47
$40,000	-2.90

The intercept from the regression report captures the utility of the baseline profile (i.e., the utility rating that a consumer would give to the baseline profile, according to our statistical model). For example, if the intercept in the regression is equal to 4.12, the utility of the baseline profile for this individual would be:

U(Model) = Baseline Intercept + u(Japanese) + u(Sedan) + u(Gasoline) + u($20,000) = 4.12

Even though each participant only evaluated 15 profiles, since we know the partworths for each individual from the coefficients in their regression reports, i.e., the value they place on each attribute level separately, we can assign a utility to any of the 81 possible car profiles for each consumer!

Consider, for example, the profile of the following model: American, SUV, hybrid, $30.000. We can estimate the utility of this profile from the regression report:

U(Model) = Baseline Intercept + u(American) + u(SUV) + u(Hybrid) + u($30,000) = 0.91

U(Model) = 4.12 + 0.60 + (-2.50) + 0.16 + (-1.47) = 0.91

Try It 5 Try It 6

All else being equal, which engine type does this consumer prefer? Refer to the regression report above.

By clicking and dragging the levels below, rank order the levels with the most preferred on top and the least preferred on the bottom.

Gas

Electric

Hybrid

Check My Answer

Step 6: Interpreting Partworths

Using the regression output, TM is now ready to assess the importance of each attribute to the respondent.

The importance of each attribute to the individual is defined as the difference between the highest and the lowest

partworths for that attribute. Intuitively, the greater this difference is the more impact on overall utility would occur when we change the level of the attribute; in other words, the more "important" the attribute is in terms of influencing preferences and choices as we move between its levels.

In our example, the importances of the various attributes for the individual are:
Brand origin: 1.16-0=1.16
Body type: 2.21-(-2.50)=4.71
Engine type: 0.91-0=0.91
Price: 0-(-2.50)=2.50

To get a better sense of how an attribute's importance level compares to that of the other attributes, market researchers often look at the relative importance of an attribute, which is equal to its importance divided by the sum of importances of all attributes. Given this definition, relative importances range between 0 and 1 and should sum up to 1. In our example:

Sum of Importances: 1.16+4.71+0.91+2.50=9.28

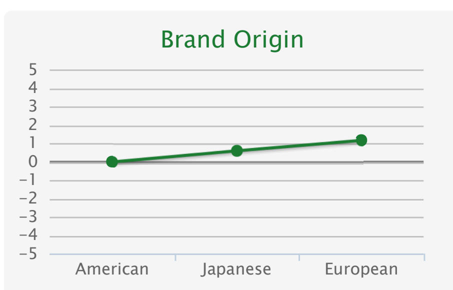
Brand origin: 1.16 / 9.28=0.12
Body type: 4.71/ 9.28= 0.51
Engine type: 0.91/ 9.28=0.10
Price: 2.50 / 9.28=0.27

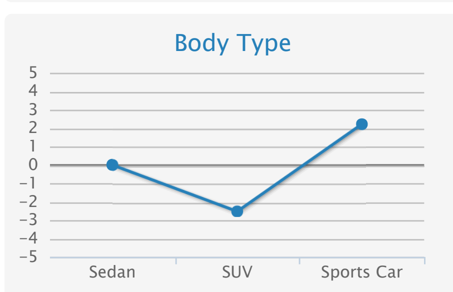
For the particular respondent above, both brand origin and engine type have low relative importance, while body type is quite important by comparison followed by price.

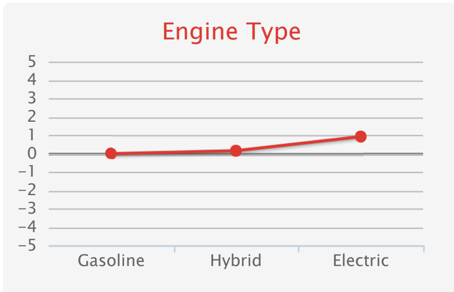
Plotting Partworths

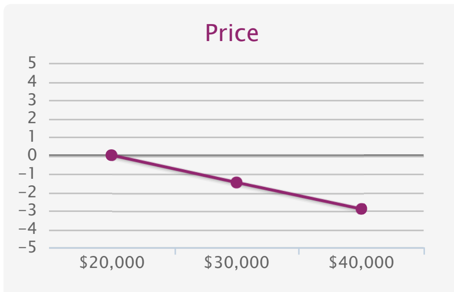
It is often helpful to plot the partworths for each attribute to get a visual representation of how each level affects utility. As can be seen from the plots below, for this individual, brand origin and engine type have rather flat graphs (consistent with the low relative importance of these attributes), while price and especially body type have nonflat curves (consistent with the high relative importance of these attributes). In other words the graphs help to visualize how sensitive the respondent's preferences are to each attribute.

For some attributes, like price, we expect plots to be monotonic (such that consumers always prefer a lower price). For other attributes that reflect variations in taste (e.g, body type), partworth plots can have any shape.









Try It 7

From looking at the graphs, what is this person's ideal car (i.e., the profile that would provide him or her the most utility)?

- **European, sedan, hybrid, $30,000**
- **Japanese, sports car, gasoline, $20,000**
- **European, sports car, electric, $20,000**
- **American, SUV, gasoline, $40,000**

Step 7: Predict Choice

TM has now built and estimated a model of one consumer's preferences for various car attributes. They can use this model to predict which automobile this individual would choose from a given set of alternatives by determining the total value (or utility) the consumer would assign to each alternative. For example, suppose the consumer had to choose one of three automobile options, as follows:

Attribute	Model A	Model B	Model C
Brand Origin	Japanese	European	American
Body Style	Sports Car	Sports Car	Sedan
Engine Type	Hybrid	Gasoline	Electric
Price	$20,000	$40,000	$30,000
Value	**6.49**	**4.59**	**4.16**

*U(**Model A**) = 4.12 + u(Japanese) + u(Sports Car) + u(Hybrid) + u($20,000) = 6.49*

*U(**Model B**) = 4.12 + u(European) + u(Sports Car) + u(Gasoline) + u($40,000) = 4.59*

*U(**Model C**) = 4.12 + u(American) + u(Sedan) + u(Electric) + u($30,000) = 4.16*

Different rules may be used to translate utility estimates into choice predictions. The simplest is the maximum utility rule, according to which the consumer simply selects the option that provides them with the highest utility. Using this rule, we would predict that this person would purchase Model A. Other more complicated rules, such as the logistic rule, use the utility estimates to assess the probability that this person would choose each option.

Try It 8

The estimated partworths of consumer 1 are listed below (the baseline levels "Sedan", "Japanese","Gasoline", and "$20,000" are assigned a utility of 0 and are therefore not listed in the table):

Consumer 1

Intercept	American	European	SUV	Sports Car	Hybrid	Electric	30000
4.56	-0.64	0.51	-0.19	0.39	1.08	2.77	-0.28

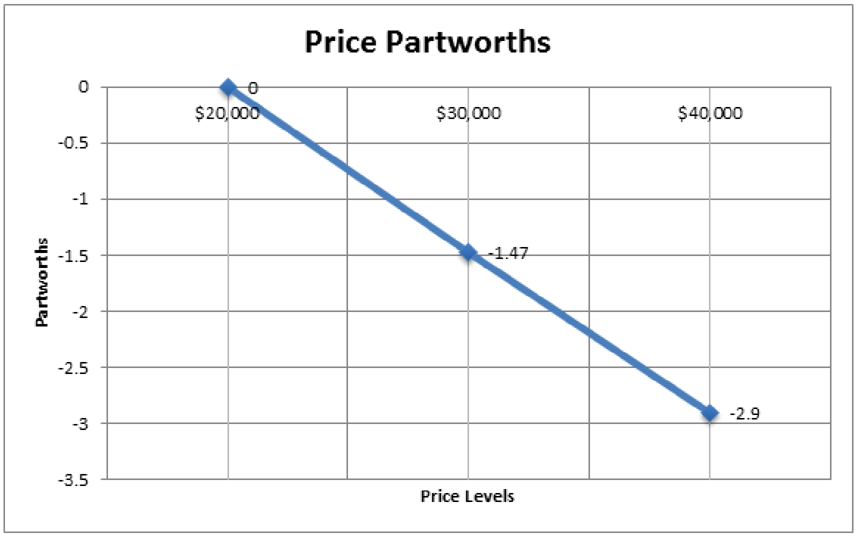
Using the maximum utility rule, which option would this consumer choose?

- **Model A: American, Sedan, Electric, $20,000**
- **Model B: European, Sports Car, Hybrid, $30,000**
- **Model C: European, SUV, Electric, $40,000**

Check My Answer

Calculating the Utility of Intermediate Attribute Levels

In the case of continuous attribute levels, we can estimate the utility corresponding to levels that are different from the ones included in the survey by using linear interpolation. In TM's case, price is the only attribute with continuous levels hence we can use interpolation to figure out every utility value to the individual for levels between $20,000 and $40,000.



In the Price Partworths graph above, the attribute levels are graphed on the x-axis and the corresponding partworths are graphed on the y-axis. As you can see, even though only discrete price levels were included in the survey, we can identify the partworth value of any intermediate price level on the x-axis, such as $25,000 or $35,000.

Suppose, for example, that Model A was priced at $25,000 instead of $20,000. We can approximate the partworth for $25,000 for a particular consumer by taking the average of the partworths for $20,000 and $30,000.

Select Regression Output for a Particular Respondent

$20,000	$30,000	$40,000
0	-1.47	-2.90

Averaging the $20,000 and $30,000 Partworths

$$U(\$25{,}000) = \frac{(0 - 1.47)}{2} = -0.74$$

If you want to estimate the partworth for $27,000, or any other value that is not exactly between two other known points, however, you will need to use the generic linear interpolation formula to get the correct utility value:

$$y = y_0 + (y_1 - y_0) \times \frac{(x - x_0)}{(x_1 - X_0)}$$

Where in our context:

- x = The intermediate continuous attribute level whose value in utils you wish to estimate
- x_1 = The closest attribute level included in the conjoint study that is greater than x
- x_0 = The closet attribute level included in the conjoint study that is less than x
- y_0 = The partworth value associated with x_0 (generated from the regression report)
- y_1 = The partworth value associated with x_1 (generated from the regression report)
- y = The partworth value you wish to estimate that corresponds to the attribute level x

Plugging in the appropriate values into the formula to estimate the partworth in utils for a price of $27,000 yields:

$$U(\$27{,}000) = 0 + (-1.47 - 0) \times \frac{(27{,}000 - 20{,}000)}{(30{,}000 - 20{,}000)} = -1.029$$

Predict Your Own Choice

Now it's your turn. Suppose you were in the market for a new vehicle and were given choices that vary on the following attributes with the following levels. Review each profile below and choose the one you most prefer (we will revisit this choice later):

Brand Origin	Body Style	Engine Type	Price	Your Choice
American	Sedan	Gasoline	$20,000	○
European	SUV	Hybrid	$30,000	○
Japanese	Sports car	Electric	$40,000	○

You Take the Survey

There is probably no better way to get a feel for what a conjoint study is all about than by actually taking one of these surveys!

We will now ask you to put yourself in the shoes of a consumer responding to a conjoint questionnaire. Once you have completed the study we will report your results on the next page.

Please rate each of the following car options by selecting the number on the 7-point preference scale (1 = lowest, 7 = highest) that best reflects your willingness to purchase that option. Each car option is described on a separate row.

#	Brand Origin	Body Type	Engine Type	Price	1	2	3	4	5	6	7
1	Japanese	Sedan	Gasoline	$20,000	○	●	○	○	○	○	○
2	European	SUV	Gasoline	$40,000	○	●	○	○	○	○	○
3	American	SUV	Electric	$30,000	○	○	●	○	○	○	○
4	European	Sports Car	Hybrid	$30,000	○	○	○	●	○	○	○
5	Japanese	Sports Car	Electric	$40,000	○	○	○	○	●	○	○

#	Brand Origin	Body Type	Engine Type	Price	1	2	3	4	5	6	7
6	American	Sedan	Gasoline	$30,000	●	○	○	○	○	○	○
7	European	Sedan	Hybrid	$40,000	○	●	○	○	○	○	○
8	Japanese	SUV	Hybrid	$20,000	○	○	●	○	○	○	○
9	American	Sports Car	Hybrid	$30,000	○	○	○	●	○	○	○
10	European	Sedan	Electric	$20,000	○	○	○	○	●	○	○

#	Brand Origin	Body Type	Engine Type	Price	1	2	3	4	5	6	7
11	Japanese	Sports Car	Gasoline	$30,000	○	○	○	○	○	●	○
12	American	Sports Car	Gasoline	$40,000	○	○	○	○	●	○	○
13	European	SUV	Electric	$30,000	○	○	○	●	○	○	○
14	Japanese	Sedan	Electric	$20,000	○	○	●	○	○	○	○
15	American	SUV	Hybrid	$30,000	○	●	○	○	○	○	○

Reset Submit »

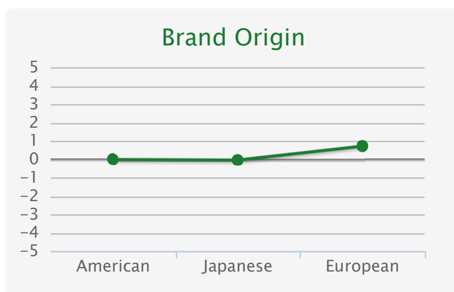
Your Preferred Car

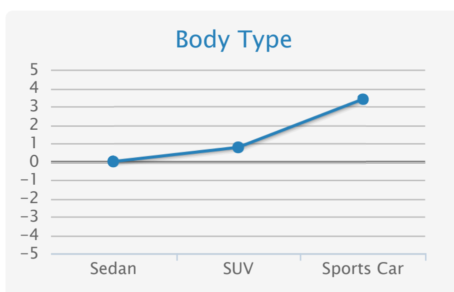
Based on your input from the previous section, we ran the regression analysis for you using American, sedan, gasoline, $20,000 as a baseline. As you discovered earlier, this profile's utility is equal to the intercept, and the other levels you see in the report are deviations from that baseline.

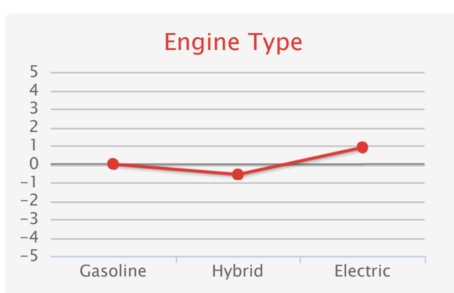
Your Regression report

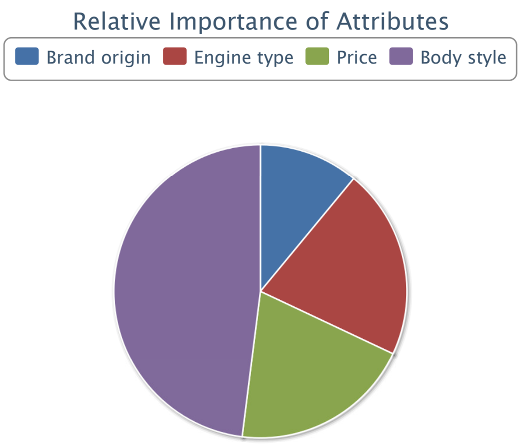
	Coefficients
Intercept	2.59
European	0.71
Japanese	-0.03
SUV	0.77
Sports Car	3.38
Hybrid	-0.55
Electric	0.90
$30,000	-1.16
$40,000	-1.41

Your Partworth Plots









Try It 9

According to the above partworth estimates, which attribute is most important to you?

- **Brand origin**
- **Body style**
- **Engine type**
- **Price**
- **All attributes are equally important**

Check My Answer

Did conjoint analysis predict your choice?

Earlier, when you were presented with three car profiles, you selected **American, Sedan, Gasoline, $20,000** as your preferred model. According to your conjoint analysis, the prediction is that you would choose **Japanese, Sports Car, Electric, $40,000**. Interestingly, over 80% of respondents' surveys will match their first prediction.

So far we have reviewed the preferences of one individual at a time. We have seen how the conjoint study output can be analyzed to characterize a number of interesting aspects of each individual's preferences and make predictions about their choices.

In real life, conjoint analysis studies are typically run with samples of consumers, often with hundreds of participants. Assuming that the sample of participants is representative of the population that is of interest to the company, by combining the preferences of all individuals it is possible to move from an individual-level to a market-level assessment. In this section, you will learn how a conjoint analysis can be used to predict choices at the market level.

Heterogeneity in Preferences

Conjoint analysis enables detecting and quantifying the existence of different segments in the population; that is, groups of individuals that are relatively similar in their preferences for products in the category (i.e. which attribute levels are more important to them).

Consider the following 40 consumer responses and their partworths as measured in a second study conducted by the car company TM:

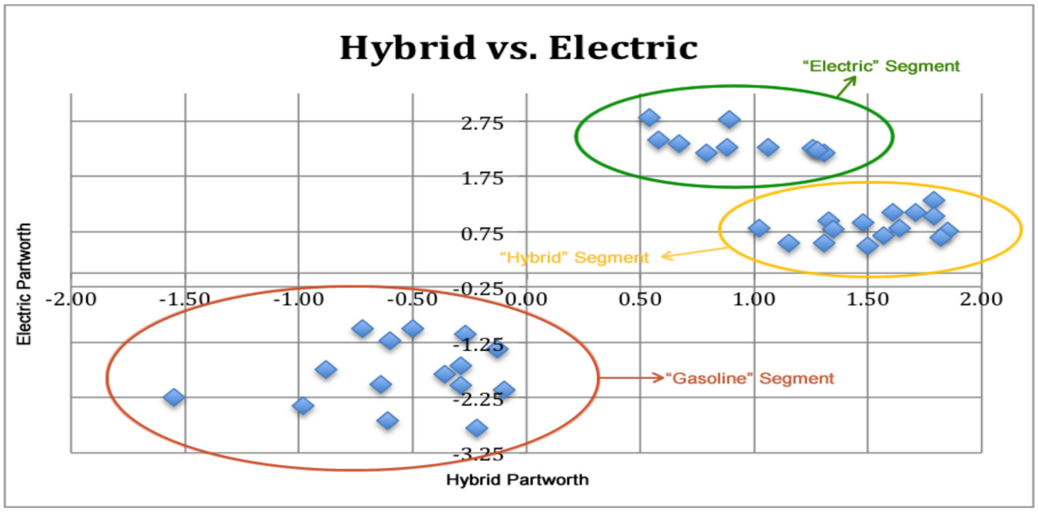
ID	Intercept	American	European	SUV	Sports Car	Hybrid	Electric	$30,000	$40,000
1	5.11	0.1	0.28	0.45	0.16	1.33	0.94	-0.49	-0.98
2	4.71	-0.65	0.57	-0.21	0.15	1.26	2.26	-0.26	-0.71
3	4.52	-0.54	0.49	-0.17	0.23	0.88	2.27	-0.19	-0.69
4	4.65	-0.55	0.64	-0.19	0.31	1.06	2.27	-0.24	-0.84
5	5.02	0.28	0.21	0.31	0.19	1.48	0.92	-0.58	-1.06
6	3.53	0.5	0.62	0.29	0.43	-0.72	-1.01	-0.57	-0.61
7	3.68	0.62	0.6	0.28	0.55	-0.27	-1.11	-0.52	-0.68
8	5.09	-0.02	0.23	0.35	0.18	1.64	0.81	-0.56	-1.07
9	5.07	0	0.29	0.45	-0.01	1.79	1.32	-0.48	-0.97
10	3.5	0.5	0.6	0.25	0.5	-0.5	-1	-0.5	-0.6
11	5.17	0.32	0.25	0.37	0.12	1.02	0.82	-0.57	-1.07
12	4.72	-0.67	0.5	-0.17	0.22	0.79	2.18	-0.32	-0.79
13	0.74	0.69	0.71	0.17	0.56	-0.29	-1.68	-0.54	-0.61
14	5.08	0.19	0.21	0.36	0.13	1.31	0.54	-0.55	-1.07
15	3.68	0.5	0.63	0.27	0.47	-0.98	-2.39	-0.54	-0.61

16	4.61	-0.67	0.52	-0.17	0.32	0.67	2.35	-0.32	-0.77
17	4.63	-0.54	0.6	-0.21	0.15	0.54	2.81	-0.26	-0.78
18	3.71	0.41	0.59	0.15	0.52	-0.13	-1.37	-0.4	-0.69
19	3.68	0.49	0.75	0.23	0.57	-0.22	-2.81	-0.54	-0.67
20	4.55	-0.62	0.66	-0.2	0.37	1.31	2.18	-0.25	-0.7
21	4.53	-0.79	0.62	-0.25	0.32	0.58	2.41	-0.31	-0.74
22	3.65	0.66	0.65	0.32	0.49	-0.1	-2.12	-0.57	-0.65
23	3.64	0.62	0.66	0.32	0.49	-0.88	-1.74	-0.43	-0.61
24	5	0.1	0.2	0.4	0.05	1.5	0.5	-0.5	-1
25	4.63	-0.76	0.61	-0.27	0.38	0.89	2.78	-0.19	-0.69
26	3.71	0.37	0.68	0.21	0.51	-0.61	-2.67	-0.56	-0.61
27	3.65	0.67	0.59	0.22	0.42	-0.29	-2.03	-0.58	-0.54
28	3.53	0.76	0.64	0.22	0.62	-0.6	-1.22	-0.44	-0.57
29	3.55	0.64	0.7	0.16	0.64	-0.64	-2.02	-0.52	-0.59
30	5.11	0.31	0.21	0.43	0.14	1.15	0.55	-0.53	-0.96
31	5.13	0.33	0.24	0.47	0.05	1.85	0.76	-0.48	-1.05
32	3.54	0.59	0.63	0.28	0.62	-0.36	-1.83	-0.54	-0.66
33	5.16	0.39	0.23	0.47	0.19	1.82	0.65	-0.53	-0.97
34	5.11	0.12	0.26	0.45	0.11	1.79	1.03	-0.42	-1.08
35	5.06	-0.08	0.26	0.4	0.2	1.57	0.67	-0.54	-1.04
36	4.73	-0.34	0.63	-0.26	0.19	1.28	2.23	-0.16	-0.73
37	3.69	0.5	0.73	0.15	0.59	-1.55	-2.24	-0.57	-0.56
38	5.1	-0.07	0.35	0.35	-0.01	1.61	1.1	-0.5	-0.95
39	5	-0.01	0.24	0.32	-0.04	1.71	1.1	-0.54	-1.02
40	5.18	-0.06	0.29	0.4	0.19	1.35	0.8	-0.52	-1.05

To get a better sense of how the preferences of the 40 consumers relate to one another we can plot their partworths for various pairs of attribute levels, such as sedan vs. Japanese.

See, for example, the scatter plot of the partworths for hybrid vs. electric engines. Each blue diamond represents the partworths of an individual from the table. Now that we can visualize how much value these features provide all the individuals in the sample, we see the emergence of three segments : some consumers prefer electric cars, some prefer hybrid cars, and some prefer gasoline engines. Also, you will notice a broader trend: some consumers prefer "green" engines in general, those in the top right quadrant, and other consumers prefer traditional gasoline engines, those in the

bottom left quadrant.



In addition to plotting various partworths, it can also be informative to plot the relative importance of various pairs of attributes.

Use of Segmentation

The identification of segments among consumers can help inform several managerial decisions, including the number of products that TM might offer and how each product should be designed and priced.

To illustrate the importance of accounting for segments, consider again our 40 representative consumers. If we ignore the existence of segments and simply average the partworths for each attribute across all consumers, the car that would provide the maximum utility on average to these consumers would be: European, Sports Car, Hybrid, for $20,000 (Model A), offering an average utility of 5.82. However, based on the three identified segments, consider the following three automobile profiles (Models B, C, and D):

- Model B is targeted to the electric segment and is: Japanese, Sports Car, Electric, for $20,000.
- Model C is targeted to the hybrid segment and is: European, SUV, Hybrid, for $20,000.
- Model D is targeted to the gasoline engine segment and is: European, Sports Car, Gasoline, for $20,000.

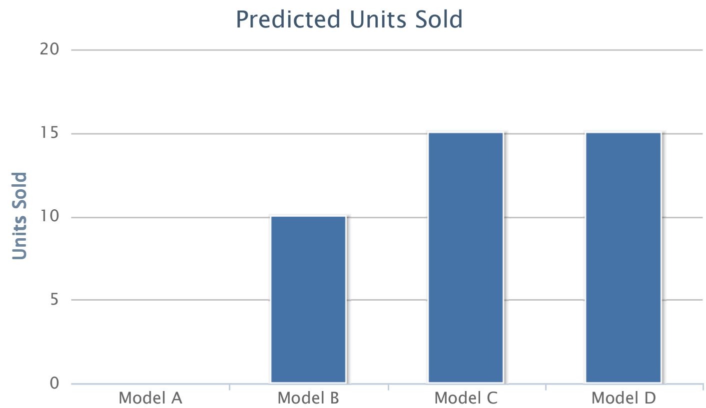
In the table below, we calculate the average utility of each model vehicle for all 40 consumers and for each of the three segments:

Model	All Consumers - Overall Average Utility	"Electric" Segment - Average Utility	"Hybrid" Segment - Average Utility	"Gasoline" Segment - Average Utility
Model A	**5.82**	6.40	6.98	4.27
Model B	4.97	**7.27**	6.04	2.35
Model C	5.70	5.93	**7.27**	3.98
Model D	5.22	5.48	5.45	**4.816**

We see that although Models B, C, and D all have a lower overall average utility compared to Model A, they each offer

higher utility to their respective segments. For instance, Model A's overall average utility of 5.82 is 0.85 utils higher than the overall average utility of Model B, at 4.97. However, when we consider only the consumers in the electric segment, we find out that their average utility for Model A is 6.40, which is lower when compared to the average utility for Model B at 7.27.

If Models A, B, C, and D were offered to TM's 40 representative consumers, how many consumers would prefer each model? To answer this question, we calculated the utility of each model for each consumer and then tallied the number of consumers who preferred each model (i.e., the car model that resulted in the maximum utility). As you can see from the graph below, 15 consumers preferred Model D, 15 consumers preferred Model C, and 10 consumers preferred model B. Interestingly, even though Model A is preferred based on the overall average, it is not preferred by a single consumer when compared with the other three models!



Finally, we can utilize the predicted number of units chosen for each car model to estimate potential market shares assuming that:

1. Your sample is representative of the target market you are addressing.
2. The products in the study are representative of the products potentially available or that would be in the consideration set of the target market.

To obtain the ***unit market share***[2] for any car model, one simply divides the number of individuals that would choose that model by the total number of individuals in the sample. So in this case, Model A would have 0% market share, Model B would have 25% market share, and Models C and D would each have 37.5% market share. Of course, the more participants one includes in the conjoint study the more reliable these market share predictions are.

Inferring Willingness to Pay

How can TM further translate these partworths into tangible information that can be used to make business decisions?

When price is one of the attributes, which is often the case, it is possible to translate each partworth from utils to willingness to pay (in $), for each consumer. Suppose that a consumer's partworth for $30,000 is -1.47 utils. This would mean that compared to a baseline of $20,000, this consumer would assign a utility of -1.47 utils to a $10,000 price increase (from $20,000 to $30,000). We can conclude that for this consumer, $10,000 is "worth" 1.47 utils.

This suggests an exchange rate between $ and utils, such that 1 util = 10,000/1.47 = $6,803. We can now apply this exchange rate to the other partworths to translate them into willingness to pay units. For example, if the partworth for "European" is 1.16, we can estimate that the consumer would be willing to pay 1.16 * 6,803 = $7,892 more for a European car vs. a Japanese car, all else equal. If instead of country of origin, we had used specific brand names as levels of the brand attribute, then our estimates of willingness to pay would be interpreted as measures of brand equity for each of these brands.

Note that the exchange rate that we obtain is slightly different based on whether it is computed by comparing the partworths for $20,000 and $30,000 vs. $30,000 and $40,000 vs. $20,000 and $40,000. As a rule of thumb, the exchange rate should be computed based on the price partworths that are closest to the targeted price point for the product or as an average of the different possible exchange rates for each pair of adjacent price partworths.

Try It 10

Given the following partworths, how much more is this consumer willing to pay for a hybrid engine vs. a gasoline engine?

Attribute Level	Partworth
Gasoline	0.00
Hybrid	0.25
$20,000	0.00
$30,000	-0.97

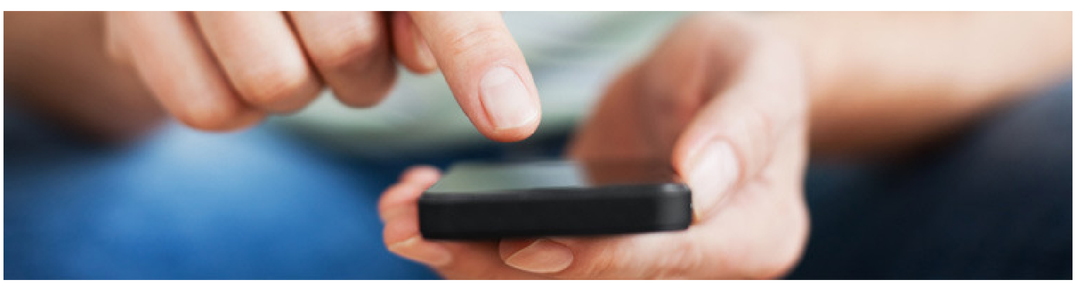
- **$10,309.28**
- **$4,725.05**
- **$2,577.32**
- **This consumer does not prefer hybrid**

Leveraging Willingness to Pay

Translating partworths into willingness to pay unlocks several opportunities for TM. For example, a group of consumers' willingness to pay for a product characteristic may be compared to the marginal cost of including that characteristic, thereby informing the decision of which features should be included or improved upon to maximize profits and return on investment if there are R&D costs involved.

Estimates of willingness to pay may also inform pricing decisions. For example, they may help determine the premium that may be charged for including any feature or set of features in a product or service.

In intellectual property litigation cases, estimates of willingness to pay are often used to quantify the additional profit a company was able to achieve by using a specific design (e.g., the recent smartphone patent infringement suit filed against Samsung).



In this tutorial you have learned about the following fundamental concepts of conjoint analysis:

- What it is and how it is used
- The definition of attributes and their levels for a product or service
- How to create product profiles and poll consumers
- The role of a regression analysis as part of a conjoint study
- How to interpret partworths and attribute importances at the individual level
- How to predict choice using conjoint output
- The experience of completing a conjoint analysis study
- Moving from individual preferences to market segmentation
- Inferring and leveraging willingness to pay

Harvard Business School Professor Elie Ofek and Columbia University Professor Olivier Toubia prepared this tutorial in conjunction with HBS IT. HBS cases are developed for the sole purpose of aiding classroom instruction. Cases are not intended to serve as endorsements, sources of primary data, or illustrations of effective or ineffective management.

Courseware # 514-712

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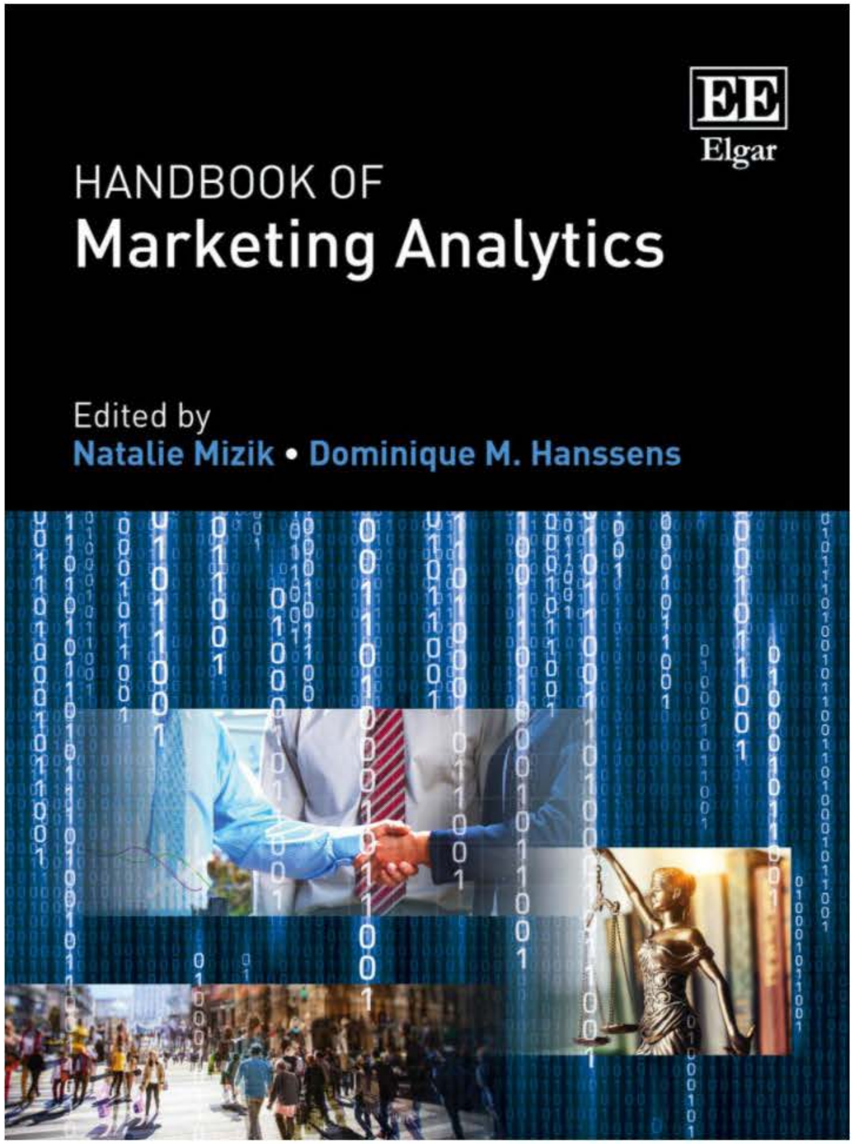
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HANDBOOK OF
Marketing Analytics
Edited by
Natalie Mizik • Dominique M. Hanssens

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Handbook of Marketing Analytics

Methods and Applications in Marketing Management, Public Policy, and Litigation Support

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Edward Elgar PUBLISHING

Cheltenham, UK • Northampton, MA, USA

Published by
Edward Elgar Publishing Limited
The Lypiatts
15 Lansdown Road
Cheltenham
Glos GL50 2JA
UK

Edward Elgar Publishing, Inc.
William Pratt House
9 Dewey Court
Northampton
Massachusetts 01060
USA

A catalogue record for this book
is available from the British Library

Library of Congress Control Number: 2017950469

This book is available electronically in the Elgaronline
Business subject collection
DOI 10.4337/9781784716752

ISBN 978 1 78471 674 5 (cased)
ISBN 978 1 78471 675 2 (eBook)

Typeset by Servis Filmsetting Ltd, Stockport, Cheshire

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Shu, L. L., N. Mazar, F. Gino, D. Ariely, and M. H. Bazerman (2012). Signing at the beginning makes ethics salient and decreases dishonest self-reports in comparison to signing at the end. *Proceedings of the National Academy of Sciences 109* (38), 15197–15200.

Simester, D., Y. J. Hu, E. Brynjolfsson, and E. T. Anderson (2009). Dynamics of retail advertising: Evidence from a field experiment. *Economic Inquiry 47* (3), 482–499.

Sun, M., X. M. Zhang, and F. Zhu (2012). To belong or to be different? evidence from a large-scale field experiment in China. *NET Institute Working Paper* (12–15).

Tadelis, S. and F. Zettelmeyer (2011). Information disclosure as a matching mechanism: Theory and evidence from a field experiment. Available at SSRN 1872465.

Toubia, O. and A. T. Stephen (2013). Intrinsic vs. image-related utility in social media: Why do people contribute content to Twitter? *Marketing Science 32* (3), 368–392.

Tucker, C. (2014a). Social Advertising. Mimeo, MIT.

Tucker, C. (2014b). Social networks, personalized advertising, and privacy controls. *Journal of Marketing Research 51* (5), 546–562.

Yao, S., C. F. Mela, J. Chiang, and Y. Chen (2012). Determining consumers' discount rates with field studies. *Journal of Marketing Research 49* (6), 822–841.

3. Conjoint Analysis

Olivier Toubia

This chapter assumes the reader has a basic understanding of the workings of Conjoint Analysis. For readers interested in a more comprehensive coverage of the topic, I recommend the exhaustive reviews of academic research in Conjoint Analysis in Agarwal et al. (2015); Bradlow (2005); Green, Krieger and Wind (2001); or Netzer et al. (2008). Conversely, readers who would like an introduction to the basics of conjoint measurement may want to consult Sawtooth Software's website (see http://www.sawtoothsoftware.com/support/technical-papers#general-conjoint-analysis and http://www.sawtoothsoftware.com/academics/teaching-aids), or Ofek and Toubia (2014a), Rao (2010), or Green, Krieger and Wind (2001).

CONJOINT ANALYSIS: OVERVIEW

Conjoint Analysis is probably one of the most used quantitative marketing research methods. Its history started in the early 1970s (Green and Rao 1971), and it has foundations in Mathematical Psychology (Luce and Tukey 1964). Many managerial applications of Conjoint Analysis have been documented over the years (e.g., Green, Krieger and Wind 2001). "Classic" applications include the design of Marriott's Courtyard Hotels (Wind et al. 1989) and the design and evaluation of the New Jersey and New York EZ-Pass system (Green, Krieger and Vavra 1999). More recent high-profile applications include the *Apple v. Samsung* patent trial (see Netzer and Sambandam 2014 for a description). Conjoint Analysis has also been adapted in creative ways that have extended the scope of its applications. For example, Yahoo! used a modified form of Conjoint Analysis to understand users' preferences for various types of news articles (Chu et al. 2009). Based on this understanding, Yahoo! was able to better customize the news articles shown on its landing page and increase the click-through rates on these articles.

Conjoint Analysis is a method for quantifying consumer preferences, i.e., for estimating utility functions. The premise of Conjoint Analysis is to decompose a product or service into *attributes* (e.g., "number of minutes included," "number of GB of data," "charge for additional minutes,"

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"base price," etc.) that each has different *levels* (e.g., "500 minutes," "1,000 minutes," "unlimited"). The output of a Conjoint Analysis study is an estimation of how much each consumer in a sample values each level of each attribute. Such preferences are called *partworths*, because they capture how much each part of the product is worth to the consumer.

Conjoint Analysis takes somewhat of an indirect approach to estimating partworths. Instead of asking consumers directly how much they value each level of each attribute, Conjoint Analysis asks consumers to evaluate *profiles*, defined by a set of attribute levels. A profile might be a "$100 plan with unlimited calls and 10 GB of data per month." Then, Conjoint Analysis relies on statistical analysis to disentangle the value of each attribute level based on consumers' evaluations of profiles. By doing that, Conjoint Analysis builds a model of consumer behavior, which can predict each consumer's preferences for any profiles, even if they were not included in the survey. For example, suppose we have five attributes with three levels each. There are $3^5 = 243$ possible profiles. We might ask consumers to evaluate 15 of these profiles, estimate their partworths for each attribute level based on these data, and then be able to predict market share for any set of profiles that contains any number of these 243 possible profiles.

The number of partworths estimated for each attribute is equal to the number of levels in that attribute *minus 1*. The loss of one degree of freedom emerges from statistical considerations, which will become clear to the statistically minded reader later in the chapter. Intuitively, each attribute in each profile must be at one level. If there are L levels in a given attribute, it is possible to describe the level of each profile on that attribute using only $L - 1$ variables. (For example, if $L = 2$ and we know whether the attribute is at the first level, we can deduce with certainty whether it is at the second level.) There are different ways to reduce the degrees of freedom. Interested readers are referred to Kuhfeld (2005). One simple way is to set one level of each attribute as the "baseline" and define each other partworth in that attribute with respect to this baseline. For example, if the partworth for "500 min" is set as the baseline, the partworth for "1,000 minutes" captures the additional utility provided to the consumer by an increase from 500 minutes to 1,000 minutes.

Mathematically, if consumers are indexed by i, profiles by j, and attributes by k, Conjoint Analysis assumes that the utility of profile j for consumer i is given as follows:

$$u_{ij} = \alpha_i + \sum\nolimits_k \beta_{ik} x_{jk} + \epsilon_{ij} \qquad (3.1)$$

Where:

- α_i is an intercept that captures the baseline utility for consumer i. Note that this intercept is not included when using Choice-Based Conjoint Analysis (see below).
- β_{ik} is a vector that captures the partworths of consumer i for attribute k. Because of the reduction in degrees of freedom mentioned earlier, if there are L levels in attribute k, this vector has one row and $L - 1$ columns.
- x_{jk} is a vector that captures the level of profile j on attribute k. If there are L levels in attribute k, this vector also has one row and $L - 1$ columns.
- ε_{ij} captures random variations.

Note that this basic model assumes that all levels of all attributes enter linearly and independently into the utility function. However, this model may be easily extended to include *interactions* between attributes. For example, if it is believed that consumers value voice minutes more in a cellular plan when more data are available, an additional *interaction* term may be included in the utility function, which would capture the joint presence of a large number of minutes and a large amount of data. In practice, these interactions are seldom used. One of the issues related to the use of interactions is that the number of possible interactions is very large. Therefore they should only be included if the researcher has a strong and valid reason to believe that specific interactions are relevant.

Note also that the additivity of the utility function implies that the basic model is compensatory, i.e., it is possible to "make up" for a lower value on one attribute by increasing the value on another attribute. However, in some cases, consumers may evaluate profiles using non-compensatory rules. Examples of non-compensatory rules include conjunctive rules (where a profile "passes" the rule if it meets a list of criteria, e.g., a car has to be of a certain body type and be below a certain price), disjunctive rules (where a profile "passes" the rule if it meets any criterion from a list, e.g., a car has to be of a certain body type or be below a certain price), disjunctions of conjunctions (where a profile "passes" the rule if satisfies at least one conjunctive rule from a set of conjunctive rules – see Hauser et al. 2010), lexicographic (where profiles are ranked based on criteria that are considered sequentially, e.g., cars are first ranked according to body type, then according to price), and elimination by aspect (where profiles are eliminated from the choice set by considering various criteria sequentially – see Tversky 1972). It has been noted that non-compensatory decision rules might actually be approximated using

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additive utility functions, such as the one assumed typically in conjoint analysis, by allowing extreme weights on certain subsets of attributes (see, for example, Bröder 2000). Nevertheless, a literature has developed for dealing specifically with non-compensatory rules (see, for example, Gilbride and Allenby 2004; Jedidi and Kohli 2005; Kohli and Jedidi 2007; Hauser 2014; Yee et al. 2007). This literature often considers the use of non-compensatory rules by consumers when they form their consideration sets (i.e., the relatively small set of alternatives to consider seriously), and assumes that choices among the alternatives in the consideration set follow a compensatory process.

There exist a wide range of options for running a Conjoint Analysis study. Surveys may be run literally within a day with very limited budget. Other surveys, in particular in litigation contexts, can take months and cost hundreds of thousands of dollars. While Conjoint Analysis surveys vary in many ways, they all involve the following steps:

1. Select attributes and levels.
2. Survey Implementation and Data Collection.
3. Partworths Estimation and Inference.

Readers are referred to Orme (2002) or Ofek and Toubia (2014b) for guidelines regarding the first step. The second and third steps will be discussed below.

I close this section by noting that there also exist market research methods that measure partworths directly instead of taking the indirect approach followed by Conjoint Analysis. These methods are referred to as "self-explicated" (Leigh, MacKay and Summers 1984; Netzer and Srinivasan 2011). Although the self-explicated approach leads to questions that are probably easier for consumers to answer and produces data that are easier to analyze, it suffers from one major limitation. In particular, when asked directly how much they care about each attribute or level, consumers have a tendency to claim that "everything is important." This leads to partworth estimates that do not discriminate as much between attributes. By forcing consumers to make tradeoffs (e.g., "this plan has more data but it is more expensive, is the difference really justified?"), Conjoint Analysis is believed to provide a more nuanced picture of consumer preferences. Note, however, that empirical comparisons of Conjoint Analysis versus the self-explicated approach have produced mixed results (e.g., Leigh, MacKay and Summers 1984; Netzer and Srinivasan 2011; Sattler and Hensel-Börner 2001), and the self-explicated approach remains a viable alternative to Conjoint Analysis.

SURVEY IMPLEMENTATION

In this section I discuss some issues related to choosing a Conjoint Analysis format, constructing an experimental design, hosting the survey and collecting the data.

Format

Several formats of Conjoint Analysis have been proposed over the years. The most traditional format is usually referred to as "ratings-based Conjoint Analysis." Ratings-based Conjoint Analysis consists of showing respondents several profiles (usually between 12 and 20) and asking them to *rate* each of them on some response scale. That is, each profile receives a preference score that may be translated into a numerical value. Profiles are assumed to be rated independently from each other by the consumer, i.e., there are no comparison between profiles.

This older format of Conjoint Analysis offers several benefits, but it suffers from some limitations. One of the main benefits is the ease with which it may be implemented and the ease with which the results may be analyzed. It is not an exaggeration to claim that with today's tools, a ratings-based Conjoint Analysis survey may be conducted from start to finish within a day and with virtually no budget. In particular, libraries exist that will provide the researcher with an efficient experimental design (see next subsection). Online platforms like Qualtrics or SurveyMonkey may be used to construct the online survey, i.e., obtain a link to the survey that may be shared with respondents. This link may be sent to lists maintained by the researcher, or panels like Amazon Mechanical Turk may be used to obtain several hundred respondents within a few hours, for a cost in the order of $1 per respondent. Finally, the analysis of ratings-based Conjoint Analysis data may be conducted using standard software such as Microsoft Excel. These benefits make ratings-based Conjoint Analysis a good choice for researchers working on a very tight deadline and with a very tight budget.

However, ratings-based Conjoint Analysis also suffers from limitations. In particular, it does not truly force respondents to make tradeoffs or to make choices that resemble real life situations. Indeed, nothing prevents the respondents from giving the same rating to all profiles. In addition, rating is not an activity in which consumers engage on a regular basis in their everyday lives (with a few notable exceptions such as product reviews). Therefore, it is questionable whether ratings-based Conjoint Analysis provides data that reflect the real-world decisions made by consumers.

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Another popular format of Conjoint Analysis, which has become the state of the art, is called Choice-Based Conjoint Analysis (CBC). (See Louviere and Woodworth 1983 for an early reference on CBC and Louviere, Hensher and Swait 2000 for a more recent and exhaustive treatment of CBC). This format asks consumers to *choose* between profiles. That is, the respondent is presented with a series of choice questions (often about 12 to 20) one after the other, where each question asks to select which profile from a small set (usually two to four) the respondent would be most likely to choose or purchase. Each choice question may also offer a "no choice" alternative, i.e., the respondent is able to indicate that they would not purchase any option in the set.

The main benefit of this format is that it is closer to the type of decisions that consumers make in real life. Indeed, most consumption decisions involve choosing one alternative over others. Accordingly, this format is considered more realistic. In addition, when a "no choice" option is included, this format does not only allow the researcher to predict relative preferences for various profiles, it also allows predicting the proportion of consumers who would actually purchase each profile. In other words, this format allows estimating primary demand.

The main disadvantage of this format is that it requires more resources to implement. In particular, the theory behind optimal experimental designs and the practical identification of optimal experimental designs are more challenging with CBC than with ratings-based Conjoint Analysis. The implementation of the survey and the data collection are not significantly more challenging. The statistical analysis of CBC data requires more advanced statistical software, and it may not be done using built-in functions in Microsoft Excel. Some studies have compared ratings-based Conjoint Analysis to CBC in terms of their ability to predict choices, with mixed results (e.g., Elrod, Louviere and Davey 1992; Moore 2004).

Several other formats of Conjoint Analysis are also worth mentioning. These include paired-comparisons (Johnson 1987; and Toubia et al. 2003) and rankings (Green and Rao 1971; Srinivasan and Shocker 1973). These formats are not used as frequently in today's environment.

In practice, researchers on a tight budget who would like to run a Conjoint Analysis study without the need for specialized software or advanced statistical knowledge would be best advised to settle for a ratings-based format. Researchers with more resources should favor a Choice-Based Conjoint format, with the realization that it tends to significantly increase the total cost of the survey.

Experimental Design

The experimental design behind a Conjoint Analysis survey specifies the set of profiles to be included. In the case of ratings-based Conjoint Analysis, it specifies the set of profiles to be rated by respondents, i.e., it specifies the level of each attribute for each profile. In the case of Choice-Based Conjoint Analysis, it specifies the sets of profiles to be included in each choice question.

Experimental designs should not be chosen randomly. First, a poorly designed set of profiles may lead to data that cannot be estimated using regression analysis. For example, if two attribute levels are perfectly correlated (e.g., all profiles with unlimited voice also have unlimited data), it will not be possible statistically to estimate the partworths of these two attribute levels separately. Second, even if the set of profiles is compatible with a regression, the confidence intervals around the estimates may be larger than optimal. That is, the experimental design may not be as *statistically efficient* as it could be. The statistical efficiency of a conjoint experimental design is a measure of the accuracy with which it allows estimating the partworths. See Kuhfeld, Tobias and Garratt (1994) for formal definitions of statistical efficiency, and Toubia and Hauser (2007) for measures of statistical efficiency that take into account the managerial goals of the study.

A large academic literature has studied ways to find optimal experimental designs, i.e., experimental designs with maximum statistical efficiency. This literature is not unique to marketing. Indeed, the issue of optimally designing experiments is relevant in many fields, including agriculture, physics, biology, psychology, etc. Interested readers are referred to Kuhfeld, Tobias and Garratt (1994) and Kuhfeld (2005).

In the case of ratings-based Conjoint Analysis, well-developed libraries of optimal experimental designs are readily accessible. Examples include the %MktEx routine in SAS (Kuhfeld 2005) and the Excel-based library provided by Ofek and Toubia (2014b). Optimal designs tend to have certain properties. For example, they tend to be "orthogonal," meaning that, for any two attributes, each pair of levels occurs in the same number of profiles (e.g., three profiles have attribute 1 at level 1 and attribute 2 at level 1, three profiles have attribute 1 at level 1 and attribute 2 at level 2, etc.).

In the case of Choice-Based Conjoint Analysis, optimizing experimental designs is more challenging, because the statistical efficiency of a CBC design depends on the true value of the partworths (Huber and Zwerina 1996; Arora and Huber 2001). It is advisable to use specialized software to create the designs in such cases. Examples include Sawtooth

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Software's CBC offering (see http://www.sawtoothsoftware.com/products/conjoint-choice-analysis/cbc).

Note that *adaptive* designs have been proposed in an effort to reduce the length of conjoint questionnaires and further increase the efficiency of the designs. These methods leverage the ability to do computations on the fly in order to customize each question based on that particular respondent's answers up to that point. Examples include Sawtooth Software ACA (Johnson 1987) and ACBC (Sawtooth Software 2014), and FastPace (Toubia et al. 2003, 2004, 2007). Other researchers have proposed intermediate solutions, in which different experimental designs are used across respondents (e.g., Sándor and Wedel 2005). Although these methods have been shown to work well, their implementation often requires customized programming, which may require additional time and programing resources.

In practice, researchers using ratings-based Conjoint Analysis should take advantage of existing libraries of optimal experimental designs. Researchers using CBC are advised to use specialized software to construct their experimental designs, such as Sawtooth. Researchers with sufficient resources may also use adaptive experimental designs, which may require customized programming.

Survey Hosting

Many options are easily accessible today to host a Conjoint Analysis survey. Some specialized software exists, such as Sawtooth Software's SSI Web suite. Alternatively, these surveys may be programmed using general online survey software such as Qualtrics (www.qualtrics.com) and SurveyMonkey (www.surveymonkey.com). Ofek and Toubia (2014b) provide examples of online Conjoint Analysis surveys developed in these platforms. Note that because Conjoint Analysis surveys tend to contain several questions, they are usually not suitable for "pre-scroll" surveys such as Google Consumer Surveys.

Data Collection

Most Conjoint Analysis studies are now performed online. Many options are available today for data collection. Some researchers have access to proprietary mailing lists of respondents, which may include their personal contacts, existing customers, etc. Other researchers use traditional online panels such as Research Now. Those hosting their surveys on Qualtrics may use that same platform as a source of respondents. In particular, Qualtrics partners with several online panel companies and offers

competitive panel services. Another alternative is Amazon Mechanical Turks (AMT). AMT is a panel maintained by Amazon. Unlike with traditional panels that tend to give "reward points" to their members, members of the AMT panel (referred to as "workers") receive well-defined financial compensation for each survey (or "HIT") that they complete. Moreover, AMT allows researchers ("requesters") to "reject" data coming from any respondent due to poor quality. This gives panel members a strong incentive to provide thoughtful answers. Accordingly, evidence suggests that the quality of the data provided by AMT is at least as good, if not superior, compared to traditional online panels (Buhrmester, Kwang and Gosling 2011; Paolacci, Chandler and Ipeirotis 2010). AMT is also very convenient, as it only takes a few hours to collect data from several hundred respondents. However, AMT does not allow researchers to limit their respondents to specific demographic groups. In particular, traditional online panels maintain basic demographic data on their members, and allow researchers to specify quotas based on these characteristics (e.g., limit the sample to specific age groups or geographical locations, or ensure that the sample of respondents matches specific distributions). AMT mainly allows researchers to limit the sample of respondents to specific countries and to recruit "master workers" with very high approval rates (i.e., their data have almost never been rejected). However, if a researcher wanted to screen respondents based on other criteria, they would need to either announce in the survey description that this survey should only be completed by certain groups of people, or they should include screening questions within the survey. The former option suffers from the issue that it is very hard to enforce and verify that only the "right" consumers took the survey. The latter option suffers from the limitation that all respondents should be compensated, even those that end up not qualifying. This oversampling greatly increases the cost per respondent. AMT has become a very common source of respondents in academia, but its adoption in industry (and in particular in litigation contexts) has been quite limited. Note that even researchers who are reluctant to using AMT for their main survey may still find it a very convenient and inexpensive way to collect pretest responses.

In practice: traditional online panels offer the "safest" source of respondents for Conjoint Analysis surveys. Amazon Mechanical Turk can be faster and cheaper and provide data of higher quality, but it does not offer as much in terms of imposing quotas based on demographics. AMT tends to be preferred by academics, while consultants and practitioners often rely on traditional online panels.

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PARTWORTHS ESTIMATION AND INFERENCE

Partworths Estimation

The data collected in a Conjoint Analysis survey consist of some evaluations (usually ratings or choices) by a group of consumers on a set of profiles. Regression analysis is used to estimate the impact of each attribute level on each respondent's evaluations. The dependent variable captures the consumers' evaluations, and the independent variables capture the description of the profiles. In the case of ratings-based Conjoint Analysis, the dependent variable is usually treated as a continuous variable, and Ordinary Least Square (OLS) regression may be used. In the case of CBC, the dependent variable is a discrete choice, and logistic regression is typically used.

One key aspect related to partworth estimation in Conjoint Analysis is how heterogeneity is addressed. Simple approaches include ignoring heterogeneity altogether by running a single aggregate regression to estimate average preferences in the market. Consumers may also be grouped based on demographic or other variables, and separate regressions may be run for each group. In the case of ratings-based Conjoint Analysis, one separate regression may be run for each respondent, providing partworth estimates at the individual level. Ofek and Toubia (2014b) provide an Excel spreadsheet that contains an example of such a regression.

However, the state of the art consists in providing individual-level estimates of partworths that are informed by the entire sample. This is typically achieved using hierarchical Bayes (Lenk et al. 1996; Rossi and Allenby 2003). Readers interested in a simple introduction to hierarchical Bayes are referred to Sawtooth Software's technical papers on this topic (see www.sawtoothsoftware.com/support/technical-papers#hierarchical-bayes-estimation). In a nutshell, hierarchical Bayes simultaneously estimates each respondent's partworths, together with the distribution of partworths among respondents. A set of partworths is estimated for each respondent, which is shrunk toward the population average. This shrinkage reduces the risk of overfitting, by imposing a penalty on parameter estimates that deviate too much from the mean. Other approaches include latent class analysis (Kamakura and Russell 1989; Andrews, Ansari and Currim 2002; Moore 2004), as well as approaches based on Machine Learning (Evgeniou, Pontil and Toubia 2007). Despite the promise held by these alternative methods, hierarchical Bayes has become the method of choice. Its implementation, which used to require extensive programming, is now much more accessible. Open-source software includes Stan (www.mc-stan.org) and OpenBUGS (www.openbugs.net). Sawtooth Software offers commercial software tailored to Conjoint Analysis.

In practice: researchers performing a ratings-based Conjoint Analysis study with limited resources may use Excel for analysis, perhaps analyzing data at the aggregate or segment level. Researchers performing a CBC study and/or researchers with access to enough resources are advised to estimate partworths using hierarchical Bayes, perhaps using existing statistical software.

Inference Based on Partworths

Estimating partworths opens many opportunities to address various managerial questions. Some of the most common types of inference based on Conjoint Analysis include:

- Optimizing the design of a single product/service,
- Optimizing the design of a line of products/services,
- Inferring willingness to pay for particular features of products/services,
- Predicting market share,
- Segmenting the market based on preferences.

All these analyses rely on the same model of consumer behavior, which specifies a utility function based on partworths, and on a link between utility and choice. In the case of CBC, the link between utility and choice is given simply by logistic probabilities. In the case of ratings-based conjoint, one may, for example, assume that when given a choice between various alternatives, a consumer would choose the one with the highest utility.

Armed with such a model of consumer choice, researchers can simulate how the market would respond to any set of profiles. In particular, demand simulators may be built that take as input the partworths of a representative sample of consumers, and that estimate the market shares of any profiles given these partworths. See Ofek and Toubia (2014b) for an example of an Excel-based market share simulator. Such simulators allow users to specify any number of profiles based on the list of attributes included in the survey. These profiles may capture existing offerings, competitors, as well as potential new offerings. Once a market share simulator has been built, it is possible to "play" with the set of profiles and see the resulting market shares immediately. In addition, several algorithms have been proposed to find the optimal product or product line, i.e., the set of profile specifications that will maximize profit (or other objective functions). See Kohli and Sukumar (1990) or Belloni et al. (2008) for a review. The implementation of these algorithms often requires customized programming.

Beyond predicting market shares and optimizing product lines, Conjoint Analysis is often used to infer willingness to pay for features of a product or service. This is feasible as long as price is one of the attributes in the survey. Suppose that the partworth for a price level p_1 is β_{p1}, and that the partworth for a price level $p_0 < p_1$ is β_{p0}. Because consumers should prefer lower prices, holding every other attribute constant, we should expect the following inequality to hold: $\beta_{p0} > \beta_{p1}$. In other words, a reduction in price from p_1 to p_0 provides a utility of $(\beta_{p0} - \beta_{p1})$ to that consumer. If we assume that utility for money is linear in the range $[p_0, p_1]$, then we can infer that a reduction of price of \$1 provides a utility of $\frac{\beta_{p0} - \beta_{p1}}{p_1 - p_0}$. If we further assume that utility for money is symmetric in gains versus losses (i.e., we assume no loss aversion), this quantity captures the "utility equivalent" of \$1 for that consumer. Conversely, we can argue that each "unit" of utility is worth $\frac{p_1 - p_0}{\beta_{p0} - \beta_{p1}}$ in dollars for that consumer. This quantity may be referred to as an "exchange rate" between utility and money. Consider another attribute where the partworth for level l_l is β_{l1}, and the partworth for level l_0 is β_{l0}. A change from level l_0 to l_l provides a utility of $(\beta_{l1} - \beta_{l0})$ to that consumer. If each "unit" of utility is worth $\frac{p_1 - p_0}{\beta_{p0} - \beta_{p1}}$ in dollars for that respondent, then if we again assume that utility is linear, we can infer that the respondent should be willing to pay $\frac{(\beta_{l1} - \beta_{l0})(p_1 - p_0)}{\beta_{p0} - \beta_{p1}}$ in dollars for a change from level l_0 to l_l. This gives us an estimate of the Willingness to Pay (WTP) for level l_l relative to level l_0 for that consumer. Once WTP is computed for each consumer in the panel, it may relevant to compute the mean, median and standard deviation of the WTP. It is also possible to build a demand curve for that attribute, i.e., the proportion of consumers in the sample who would be willing to pay at least price p for that attribute, where p varies.

Another approach for making monetary inferences based on the output of a Conjoint Analysis survey is to rely again on a market share simulator. In particular, instead of estimating a WTP for each consumer in the panel for a specific feature, we can determine by how much price would have to be decreased in order to make up for a reduction in one feature (or a combination of features). In order to achieve this, we can specify a set of competing alternatives, e.g., five existing plans offered by our competitors, and a focal alternative, e.g., a plan offered by our company. We can estimate the market share of our plan assuming certain levels for each attribute, e.g., unlimited voice and unlimited data. Then, we can reduce one of the features of our plan, e.g., only 10 GB of data instead of unlimited data. Naturally, we would expect the predicted share of our plan to drop. We can then use the simulator to determine by how much we would need to decrease the price of our plan with 10 GB in order to raise the share back to the original level (with unlimited data). Toubia, Hauser and Garcia (2007) used a similar method to determine the discount that should be offered to convince wine customers to switch from cork to screw caps. A similar approach was used in an expert report on the famous *Apple v. Samsung* case, to determine how much consumers value certain features of smartphones such as "pinch-to-zoom." Readers are referred to Netzer and Sambandam (2014) for a short and simplified discussion. This approach is not without its critics, however. Notably, Allenby et al. (2014) warn against ignoring competitive response to changes in product attributes and stress the need to consider equilibrium profits when using Conjoint Analysis to value product features.

Finally, once partworths have been estimated, researchers sometimes find it useful to explore the existence of distinct segments in the population. This may provide valuable insights to marketers and constitutes one viable way to segment markets (other ways include demographic segmentation, psychographic segmentation, etc.). For this, any segmentation approach such as k-means clustering may be used.

In practice, calculations of willingness to pay may be completed very easily using any data handling software. Market share simulators may be implemented within Microsoft Excel or more complex technical programming software. Market share simulators may also be used to approximate the market value of an attribute, by determining the loss in profit (i.e., price reduction) for a company that would reduce their offering on this attribute. Segmentation may be conducted using any available statistical software.

ECOLOGICAL VALIDITY AND THE ISSUE OF ATTENTION

The first question on many people's minds is whether Conjoint Analysis does a good job predicting real-life choices, i.e., whether it has good ecological validity. Ideally, testing ecological validity requires comparing predictions from a Conjoint Analysis survey to choices made by consumers in the real world. Creating such a situation is challenging, as real-life environments rarely mimic the sterilized and simplified format of Conjoint Analysis. However, several studies have been able to test the ecological validity of Conjoint Analysis, and their results have been quite positive. See Louviere (1988) or Green and Srinivasan (1990) for a review. In addition, many studies have tested the *external* validity of Conjoint Analysis, i.e., its ability to predict choices in other contexts, which are not necessarily real-world decisions.

In addition to comparing predictions from Conjoint Analysis to actual

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behavior, researchers have studied more generally the issue of how much attention consumers spend in Conjoint Analysis surveys, and whether their level of attention in the survey is similar to how they would approach choices in real life. Such evidence will be reviewed later in this section. First, we review recent attempts to motivate participants to pay more attention to surveys and take the task more seriously.

Incentive Alignment

Traditional surveys do not link the respondents' compensation to their answers. That is, from the perspective of the respondent, there are often very few consequences to their answers. While most respondents probably have a good nature and good intentions, there are so many demands on consumers' time and attention today that it is hard to assume that all consumers will spontaneously answer all survey questions in a way that is exactly consistent with how they would behave in real life. Why would a rational person care to think hard about the questions in a survey, if there is nothing to gain from it? In addition to attention, social desirability is another obvious concern. Consumers may be embarrassed to reveal certain preferences and to admit to the researcher (and to themselves) that they care more or less about certain attributes. Examples include price sensitivity (consumers may not want to admit their true level of price sensitivity), and any other preference that is related to some social norms (e.g., how much consumers care about the environment, fair trade, etc.).

One way to start tackling these issues is incentive alignment, i.e., linking the consumer's compensation for taking a survey to their answers in the survey. Incentive alignment has a long tradition in economics. Some of the first documented uses in the marketing context of Conjoint Analysis include Toubia et al. (2003) and Ding, Grewal and Liechty (2005). In particular, Ding, Grewal and Liechty (2005) proposed an incentive-aligned conjoint mechanism, whereby each choice made by each respondent during the Conjoint Analysis survey has some positive probability of being realized (i.e., the respondent may actually receive his or her chosen alternative). That is, each respondent has some probability of being selected as a "winner." When that happens, one of their choices is randomly selected, and they receive their favorite alternative from that choice. Ding, Grewal and Liechty (2005) showed that this mechanism increases external validity in choice-based conjoint (CBC) experiments, compared to a benchmark with no incentive alignment. While it paved the way for incentive alignment research in Conjoint Analysis, the initial mechanism proposed by Ding, Grewal and Liechty (2005) is not very practical, as it requires being able to offer any possible profile as a possible

compensation. Consequently, Ding (2007) extended this method by allowing researchers to reward respondents from a limited set of products. Ding (2007)'s mechanism involves inferring the respondent's willingness to pay for one or a few reward profiles. Dong, Ding and Huber (2010) further improved the practicality of incentive alignment by proposing an alternative approach, based on an inferred rank order of the potential reward profiles, which does not require the estimation of willingness to pay. One potential concern with incentive alignment would be that consumers systematically select more expensive alternatives, in order to increase the market (and therefore resale) value of the prize they will receive if they are selected as winners. This is addressed by giving each winner a fixed monetary prize, using that money to purchase their preferred alternative from one of their choice questions, and giving them the change in cash. For example, Toubia et al. (2003) gave each winner $100, with which they purchased a laptop bag priced between $70 and $100 which was selected based on respondents' answers, and gave the difference between $100 and the price of the laptop bag as cash to respondents.

Incentive alignment has become the gold standard in Conjoint Analysis. Indeed, it has been shown to lead to significant improvements in the realism of Conjoint Analysis surveys, although some eye-tracking evidence reviewed later in this section suggests it may not be enough to induce consumers to treat Conjoint Analysis choices exactly like they would treat real-life choices. One key limitation of incentive alignment is logistical. The costs and logistics of distributing products to consumers may become prohibitive, in particular as the sample grows (although usually only a fraction of consumers are randomly selected to get a prize), and for more expensive product categories. One creative solution was provided by Ding et al. (2011). These authors studied preference for automobiles, where incentive alignment required putting a positive probability on the event that one respondent would receive $40,000 toward the purchase of an actual automobile. In order to offer such incentives, the authors purchased prize indemnity insurance on the open market, for a fixed fee. That is, the authors paid the insurance company a fixed fee, and the insurance company was responsible for paying the $40,000 prize if a respondent actually won it.

Gamification

Incentive alignment provides an extrinsic motivation to respondents to be truthful in their answers and to take surveys seriously. Another way to increase attention is to increase intrinsic motivation, by gamifying the experience. In particular, the first use of online surveys was to perform

the same type of surveys that used to be conducted offline, in an online environment. However, with online studies, it is possible to perform computations on the fly during the survey, and to connect respondents with one another as they go through the task. Researchers are now starting to leverage the web more fully to invent new tasks that take advantage of its capabilities. For example, Ding, Park and Bradlow (2009) proposed an online incentive-aligned method inspired by barter markets. Park, Ding and Rao (2008) introduced a preference measurement mechanism that relies on upgrading decisions: respondents state their willingness to pay for an upgrade, and the transaction is realized if a randomly generated price is smaller than stated willingness to pay. Toubia et al. (2012) developed and tested an incentive-aligned conjoint poker game to measure preferences. This game collects data that are similar to CBC, but in a gamified context. Traditional poker uses regular playing cards. From a Conjoint Analysis perspective, playing cards are profiles with two attributes (Color with four levels, and Number with 13 levels). These authors develop a version of poker where cards may have any number of attributes and levels (e.g., Design, Color and Price). Similar to poker, players create hands based on similarities and differences between cards. In the process of creating these hands, players are required to pay attention to the profiles captured on these cards, which increases their motivation to process all the available information.

Screening for Attention

In addition to providing incentives to respondents and making the survey-taking experience more enjoyable, several routine measures exist to check for attention and screen out inattentive respondents. First, it is common to start an online survey with a "CAPTCHA." While the primary purpose of this type of questions is to ensure that the survey is completed by humans instead of by internet bots, it also provides a very basic attention check. Second, it is advisable to insert at least one "attention check" question (also called "Instructional Manipulation Check") at the end of the survey. These questions are often multiple-choice questions with an open-ended option. The instructions to these questions are often a few lines, that may include a statement like: "If you have read this question carefully, please . . ." These questions are designed such that only respondents who have carefully read the instructions are able to provide a "correct" response, and those who fail to do that may be dropped from the sample. Oppenheimer, Meyvis and Davidenko (2009) show that the inclusion of such questions can increase the statistical power and reliability of a survey dataset. Third, respondents who completed the survey suspiciously fast

may be automatically discarded. There is no universal cutoff for response time. Some researchers like to drop respondents with a log of response time that is less than 1 or 1.5 standard deviations from the mean. The commercial survey-hosting platform Qualtrics drops respondents with response time less than one-third of the average from the initial "soft launch" of the survey (i.e., the first 60 or so respondents).

Eye Tracking Evidence

Eye-tracking research has a long tradition in advertising and branding (e.g., Pieters and Warlop 1999; Wedel and Pieters 2000; Pieters and Wedel 2004; Van der Lans, Pieters, and Wedel 2008). More recently, researchers have started using eye tracking in Conjoint Analysis in order to directly measure how respondents allocate their attention during surveys.

Eye-tracking data are composed of fixations and saccades (Wedel and Pieters 2000). Fixations represent the time periods in which participants fix their eyesight on a specific location; saccades represent eye movements between two fixations. As mentioned above, Toubia et al. (2012) used eye tracking to measure attention in regular CBC versus their Conjoint Poker game. Profile information is usually presented in a matrix format (e.g., one column per choice alternative and one row per attribute). Toubia et al. (2012) found that participants in their Conjoint Poker had on average at least one fixation on approximately 90 percent of the cells in the matrix containing the choice-relevant information. However, this proportion dropped to 60–70 percent for participants in an incentive-aligned CBC condition. Yang, Toubia and De Jong. (2015) found similar results. That is, even when incentives are aligned, participants in CBC tend to ignore 30–40 percent of the choice-relevant information provided to them. Meißner, Musalem and Huber (2016) present eye-tracking evidence that suggests that respondents tend to adjust their decision processes to increase speed while maintaining reliability. Shi, Wedel and Pieters (2013) show that the information acquired by respondents is influenced by the format in which the information is presented (i.e., whether attributes are in rows and alternatives in columns, or the other way around). Stüttgen, Boatwright and Monroe (2012) provide eye tracking evidence that supports a satisficing model of choice, according to which respondents stop evaluating choice alternatives once they have found one that is satisfactory. In such a model, the final choice is influenced by the order in which alternatives are considered.

The eye-tracking evidence provided in these studies suggests that respondents in Conjoint Analysis surveys do not process all the relevant information presented to them even in the presence of incentive align-

ment, and that their information processing may be easily influenced by incidental factors. This raises the question of whether consumers ignore some relevant information in real-life choices as well. In other words, do consumers also ignore 30–40 percent of the relevant information when making real-life choices?

All incentive-aligned preference measurement methods follow an approach known in economics as the random lottery mechanism (RLM). In an RLM, each choice has some probability of being realized and at most one choice is realized per subject. In other words, incentive alignment uses tasks that are "probabilistically" incentive aligned, i.e., each choice only has some (usually small) probability of being realized. In contrast, most real-life decisions involve what may be labeled as "deterministic" incentives, i.e., the transaction will happen with probability 1. Yang, Toubia and De Jong (2017) argue that if it takes effort for consumers to process information during a Conjoint Analysis task, we should expect attention levels in probabilistically incentive-aligned tasks to be lower than they are in deterministically incentive-aligned tasks. Indeed, the cognitive costs involved in processing information are the same irrespective of the incentives. On the other hand, the benefits from these efforts are larger when choices are more likely to be realized. Therefore, a boundedly rational consumer should invest less effort in processing information when choices are less likely to be realized. In order to test this hypothesis, Yang, Toubia and De Jong (2017) ran an eye-tracking study in which each respondent makes a single choice that may be realized with probability 0, 0.01, 0.50, 0.99, or 1. They find that, indeed, the amount of information processed and the time taken to make a decision are positively correlated with this probability, and that the probabilistic incentives that are typically used in Conjoint Analysis (where the probability that each choice will be realized in usually in the order of 0.01) are not enough to motivate consumers to treat these choices as they would treat real-life choices. Nevertheless, incentive alignment remains the state of the art in choice experiments.

One may wonder whether a solution to this problem would be to make all Conjoint Analysis choices deterministically incentive-aligned. That is, each choice question would be realized with certainty. In addition to being prohibitively costly, this approach would also be incorrect methodologically. Indeed, when multiple questions are asked in a Conjoint Analysis survey, a basic assumption is that these choices are independent. However, if each choice is realized, this assumption would be violated. For example, a consumer who chose an SLR camera in the first question may choose a compact camera in the next question, since their utility for a new SLR camera diminishes once they already have one.

A more promising solution to the attention problem would be to

develop models of information search and choice such as the ones of Stüttgen et al. (2012) or Yang, Toubia and De Jong (2015). These models capture both how consumers acquire information and how they choose based on this information. Such models may be extended to allow for counterfactual simulation, or extrapolation, where real-life search and choices would be predicted based on data coming from probabilistically aligned incentive-aligned choices.

However, this approach may not be enough to close the gap between probabilistic and deterministic incentives. Indeed, Yang, Toubia and De Jong (2017) show that the probability that the choice will be realized does not only impact what and how much information consumers pay attention to, it also impacts *how* they choose. In particular, these authors find that respondents for whom choices are more likely to be realized also tend to choose more familiar products and tend to be more price sensitive. These findings are consistent with previous findings by Ding, Grewal and Liechty (2005) who report that consumers show a greater willingness to try new things, exhibit less price sensitivity, and exhibit more socially desirable behaviors when choices are purely hypothetical as opposed to probabilistically incentive-aligned. These effects may be explained using the concept of Psychological Distance (Trope and Liberman, 2010). It has been shown that improbable events tend to be more psychologically distant than probable ones, i.e., the lower the probability of the event, the greater its psychological distance (Todorov, Goren and Trope 2007; Wakslak et al. 2006). In turn, it has been shown that when choices are more psychologically distant, consumers are more likely to choose based on abstract, high-level, positive considerations (referred to as desirability concerns), versus more concrete, practical, negative ones (referred to as feasibility concerns in the literature). This theory explains the results reported by Yang, Toubia and De Jong (2017) and by Ding, Grewal and Liechty (2005). Indeed, price is a pragmatic, negative, feasibility-oriented attribute, and therefore we should expect consumers to be more price sensitive when choices are less psychologically distant (i.e., more likely to be realized). Similarly, trying new things and behaving in a socially desirable manner tend to be desirability-oriented features, which should receive more weight when choices are more psychologically distant (i.e., less likely to be realized). These findings imply that it may not be enough to predict the level of attention that consumers would pay in real-life choices in order to predict these choices. It may also be necessary to model how preferences are impacted by probabilistic versus deterministic incentives.

To close on a positive note, eye tracking also provides valuable information that may be leveraged to improve our ability to measure consumers' preferences efficiently. For example, Yang, Toubia and De Jong's (2015)

model links partworths and eye movements, which enables the researcher to learn about the respondent's preferences from their eye movements. Yang, Toubia and De Jong (2015) find that this additional information allows reducing the length of Conjoint Analysis questionnaires. In their study, they find that leveraging eye tracking data allows extracting as much information in 12 choice questions as would be extracted in 16 choice questions without eye tracking data. Such a model is becoming increasingly feasible in practice, as eye-tracking technology becomes more easily accessible. In particular, it is now possible to conduct eye-tracking studies using the camera on the respondent's computer or smartphone (e.g., www.eyetrackshop.com, www.youeye.com).

In practice: whenever feasible, it is recommended to use incentive alignment in Conjoint Analysis, despite the implied costs. It is also recommended to design surveys that are attractive and engaging in order to motivate respondents to pay more attention to the task. Researchers should also implement measures and tests of attention and drop respondents who appear to have been inattentive. Despite these best practices, it is important to keep in mind that Conjoint Analysis remains a marketing research tool, which can at best *approximate* real-life decisions. The first-best option would be to manipulate choice options in real-life and observe the resulting consumer choices. Short of this, incentive-aligned Conjoint Analysis may be viewed as a second-best solution.

CONCLUSIONS

After 45 years, Conjoint Analysis remains a major quantitative marketing research method and a major area of academic research in marketing. New, exciting research is expected, enabled by new technological developments that make the collection of physiological data feasible on a large scale (e.g., eye tracking, skin conductance, brain responses). This chapter has reviewed a selected set of issues related to implementing a Conjoint Analysis survey and making quantitative, managerially relevant inferences based on the data. Particular emphasis was placed on issues of ecological validity and attention. Recent tools for motivating respondents to behave in Conjoint Analysis surveys like they would behave in real life were reviewed, including incentive alignment and gamification. Despite these advances, it is important to keep in mind that a Conjoint Analysis survey will always remain a survey tool, which at best approximates real-life choices. Conjoint Analysis may not be perfect, but it may also be one of the most efficient and reliable methods available today for quantifying consumer preferences.

The *Apple v. Samsung* case provided another demonstration of the value of Conjoint Analysis, which greatly increased interest in this method, in particular among the legal community. Hopefully this chapter will help prospective users decide whether Conjoint Analysis is the right approach for them. Such decision requires being aware of other available options. In particular, it is important to keep in mind that Conjoint Analysis is particularly suited for situations in which customers routinely make tradeoffs between various attributes of a product or service, and when these attributes may be described in objective terms (e.g., number of minutes, number of pixels, miles per gallon). In some situations, tradeoffs are less relevant, perhaps because there is only one main attribute in the product/service, or the focal attribute is not really comparable to other attributes. In such cases, simpler methods may be considered, such as the Contingent Valuation Method (Arrow et al. 1993; Mitchell and Carson 1989). In other cases, attributes are harder to define objectively, perhaps because they involve aesthetics and/or sensory considerations. In such cases, more qualitative approaches may be considered as alternatives to Conjoint Analysis.

REFERENCES

Agarwal, James, et al. "An Interdisciplinary Review of Research in Conjoint Analysis: Recent Developments and Directions for Future Research." *Customer Needs and Solutions* 2.1 (2015): 19–40.

Allenby, Greg M., et al. "Valuation of Patented Product Features." *Journal of Law and Economics* 57.3 (2014): 629–663.

Andrews, Rick L., Asim Ansari, and Imran S. Currim. "Hierarchical Bayes versus finite mixture Conjoint Analysis models: A comparison of fit, prediction, and partworth recovery." *Journal of Marketing Research* 39.1 (2002): 87–98.

Arora, Neeraj and Joel Huber. "Improving parameter estimates and model prediction by aggregate customization in choice experiments." *Journal of Consumer Research* 28.2 (2001): 273–283.

Arrow, Kenneth, et al. "Report of National Oceanic and Atmospheric Administration panel on the reliability of natural resource damage estimates derived from contingent valuation." *Federal Register* 58 (1993): 4601–4614.

Belloni, Alexandre, et al. "Optimizing product line designs: Efficient methods and comparisons." *Management Science* 54.9 (2008): 1544–1552.

Bradlow, Eric T. "Current issues and a 'wish list' for Conjoint Analysis." *Applied Stochastic Models in Business and Industry* 21.4–5 (2005): 319–323.

Bröder, Arndt. "Assessing the empirical validity of the 'Take-the-best' heuristic as a model of human probabilistic inference." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 26.5 (2000): 1332.

Buhrmester, Michael, Tracy Kwang, and Samuel D. Gosling. "Amazon's Mechanical Turk: a new source of inexpensive, yet high-quality, data?" *Perspectives on Psychological Science* 6.1 (2011): 3–5.

Chu, Wei, et al. "A case study of behavior-driven Conjoint Analysis on Yahoo!: Front Page Today Module." *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2009.

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Ding, Min, "An incentive-aligned mechanism for Conjoint Analysis." *Journal of Marketing Research* 44.2 (2007): 214–223.
Ding, Min, Rajdeep Grewal, and John Liechty. "Incentive-aligned Conjoint Analysis." *Journal of Marketing Research* 42.1 (2005): 67–82.
Ding, Min, Young-Hoon Park, and Eric T. Bradlow. "Barter markets for Conjoint Analysis." *Management Science* 55.6 (2009): 1003–1017.
Ding, Min, et al. "Unstructured direct elicitation of decision rules." *Journal of Marketing Research* 48.1 (2011): 116–127.
Dong, Songting, Min Ding, and Joel Huber. "A simple mechanism to incentive-align conjoint experiments." *International Journal of Research in Marketing* 27.1 (2010): 25–32.
Elrod, Terry, Jordan J. Louviere, and Krishnakumar S. Davey. "An empirical comparison of ratings-based and choice-based conjoint models." *Journal of Marketing Research* 29.3 (1992): 368–377.
Evgeniou, Theodoros, Massimiliano Pontil, and Olivier Toubia. "A convex optimization approach to modeling consumer heterogeneity in conjoint estimation." *Marketing Science* 26.6 (2007): 805–818.
Gilbride, Timothy J. and Greg M. Allenby. "A choice model with conjunctive, disjunctive, and compensatory screening rules." *Marketing Science* 23.3 (2004): 391–406.
Green Paul, E., A. M. Krieger, and T. Vavra. "Evaluating EZ-Pass: using Conjoint Analysis to assess consumer response to a new tollway technology." *Marketing Research* 11.2 (1999): 5–16.
Green, Paul E., Abba M. Krieger, and Yoram Wind. "Thirty years of Conjoint Analysis: Reflections and prospects." *Interfaces* 31.3 supplement (2001): S56–S73.
Green, Paul E., and Vithala R. Rao. "Conjoint measurement for quantifying judgmental data." *Journal of Marketing Research* (1971): 355–363.
Green, Paul E. and Venkat Srinivasan. "Conjoint Analysis in marketing: new developments with implications for research and practice." *Journal of Marketing* (1990): 3–19.
Hauser, John R. "Consideration-set heuristics." *Journal of Business Research* 67.8 (2014): 1688–1699.
Hauser, John R., Olivier Toubia, Theodoros Evgeniou, Rene Befurt, and Daria Dzyabura. "Disjunctions of conjunctions, cognitive simplicity, and consideration sets." *Journal of Marketing Research* 47.3 (2010): 485–496.
Huber, Joel and Klaus Zwerina. "The importance of utility balance in efficient choice designs." *Journal of Marketing research* (1996): 307–317.
Jedidi, Kamel and Rajeev Kohli. "Probabilistic subset-conjunctive models for heterogeneous consumers." *Journal of Marketing Research* 42.4 (2005): 483–494.
Johnson, Richard M. "Adaptive Conjoint Analysis." *Sawtooth Software Conference Proceedings*. Sawtooth Software, Ketchum, ID, 1987.
Kamakura, Wagner A. and Gary Russell. "A probabilistic choice model for market segmentation and elasticity structure." *Journal of Marketing Research* 26 (1989): 379–390.
Kohli, Rajeev and Kamel Jedidi. "Representation and inference of lexicographic preference models and their variants." *Marketing Science* 26.3 (2007): 380–399.
Kohli, Rajeev and Ramamirtham Sukumar. "Heuristics for product-line design using Conjoint Analysis." *Management Science* 36.12 (1990): 1464–1478.
Kuhfeld, Warren F. "Marketing research methods in SAS." *Experimental Design, Choice, Conjoint, and Graphical Techniques*. Cary, NC, SAS-Institute TS-722 (2005).
Kuhfeld, Warren F., Randall D. Tobias, and Mark Garratt. "Efficient experimental design with marketing research applications." *Journal of Marketing Research* (1994): 545–557.
Leigh, Thomas W., David B. MacKay, and John O. Summers. "Reliability and validity of Conjoint Analysis and self-explicated weights: A comparison." *Journal of Marketing Research* (1984): 456–462.
Lenk, Peter J., et al. "Hierarchical Bayes Conjoint Analysis: Recovery of partworth heterogeneity from reduced experimental designs." *Marketing Science* 15.2 (1996): 173–191.
Louviere, Jordan J. "Conjoint Analysis modelling of stated preferences: a review of theory,

methods, recent developments and external validity." *Journal of Transport Economics and Policy* (1988): 93–119.
Louviere, Jordan J., David A. Hensher, and Joffre D. Swait. *Stated choice methods: analysis and applications*. Cambridge University Press, 2000.
Louviere, Jordan J. and George Woodworth. "Design and analysis of simulated consumer choice or allocation experiments: an approach based on aggregate data." *Journal of Marketing Research* (1983): 350–367.
Luce, R. Duncan and John W. Tukey. "Simultaneous conjoint measurement: A new type of fundamental measurement." *Journal of Mathematical Psychology* 1.1 (1964): 1–27.
Meißner, Martin, Andres Musalem, and Joel Huber. "Eye-Tracking Reveals Processes that Enable Conjoint Choices to Become Increasingly Efficient with Practice." *Journal of Marketing Research*. 53.1 (2016): 1–17.
Mitchell, Robert Cameron and Richard T. Carson (1989), *Using Surveys to Value Public Goods: The Contingent Valuation Method*, Resources for the Future, Washington, DC.
Moore, William L. "A cross-validity comparison of rating-based and choice-based Conjoint Analysis models." *International Journal of Research in Marketing* 21.3 (2004): 299–312.
Netzer, Oded and Rajan Sambandam. "Apple vs. Samsung: The $2 Billion Case." Columbia CaseWorks (2014).
Netzer, Oded and Visvanathan Srinivasan. "Adaptive self-explication of multiattribute preferences." *Journal of Marketing Research* 48.1 (2011): 140–156.
Netzer, Oded, et al. "Beyond Conjoint Analysis: Advances in preference measurement." *Marketing Letters* 19.3–4 (2008): 337–354.
Ofek, Elie and Olivier Toubia. "Conjoint Analysis: Online Tutorial." Harvard Business School Tutorial 514–712. (2014a).
Ofek, Elie and Olivier Toubia. "Conjoint Analysis: A Do it Yourself Guide." Harvard Business School Technical Note 515–024. (2014b).
Oppenheimer, Daniel M., Tom Meyvis, and Nicolas Davidenko. "Instructional Manipulation Checks: Detecting Satisficing to Increase Statistical Power." *Journal of Experimental Social Psychology* 45 (2009): 867–872.
Orme, Bryan. "Formulating attributes and levels in Conjoint Analysis." *Sawtooth Software Research Paper* (2002): 1–4.
Paolacci, Gabriele, Jesse Chandler, and Panagiotis G. Ipeirotis. "Running experiments on Amazon Mechanical Turk." *Judgment and Decision Making* 5.5 (2010): 411–419.
Park, Young-Hoon, Min Ding, and Vithala R. Rao. "Eliciting preference for complex products: A web-based upgrading method." *Journal of Marketing Research* 45.5 (2008): 562–574.
Pieters, Rik and Luk Warlop. "Visual attention during brand choice: The impact of time pressure and task motivation." *International Journal of Research in Marketing* 16.1 (1999): 1–16.
Pieters, Rik and Michel Wedel. "Attention capture and transfer in advertising: Brand, pictorial, and text-size effects." *Journal of Marketing* 68.2 (2004): 36–50.
Rao, Vithala R. "Conjoint Analysis." *Wiley International Encyclopedia of Marketing* (2010).
Rossi, Peter E., and Greg M. Allenby. "Bayesian statistics and marketing." *Marketing Science* 22.3 (2003): 304–328.
Sándor, Zsolt and Michel Wedel. "Heterogeneous conjoint choice designs." *Journal of Marketing Research* 42.2 (2005): 210–218.
Sattler, Henrik and Susanne Hensel-Börner. "A comparison of conjoint measurement with self-explicated approaches." *Conjoint Measurement*. Springer (2001): 121–133.
Sawtooth Software. "The Adaptive Choice-Based Conjoint (ACBC) Technical Paper." *Sawtooth Software Technical Paper Series* (2014). Available at: http://www.sawtoothsoftware.com/support/technical-papers/adaptive-cbc-papers/acbc-technical-paper-2009 (last accessed October 3, 2017).
Shi, Savannah Wei, Michel Wedel, and F. G. M. Pieters. "Information acquisition during online decision making: A model-based exploration using eye-tracking data." *Management Science* 59.5 (2013): 1009–1026.

Srinivasan, Venkataraman and Allan D. Shocker. "Linear programming techniques for multidimensional analysis of preferences." *Psychometrika* 38.3 (1973): 337–369

Stüttgen, Peter, Peter Boatwright, and Robert T. Monroe. "A satisficing choice model." *Marketing Science* 31.6 (2012): 878–899.

Todorov, Alexander, Amir Goren, and Yaacov Trope. "Probability as a psychological distance: Construal and preferences." *Journal of Experimental Social Psychology* 43.3 (2007): 473–482.

Toubia, Olivier and John R. Hauser. "Research note-on managerially efficient experimental designs." *Marketing Science* 26.6 (2007): 851–858.

Toubia, Olivier, John Hauser, and Rosanna Garcia. "Probabilistic polyhedral methods for adaptive choice-based Conjoint Analysis: Theory and application." *Marketing Science* 26.5 (2007): 596–610.

Toubia, Olivier, John R. Hauser, and Duncan I. Simester. "Polyhedral methods for adaptive choice-based Conjoint Analysis." *Journal of Marketing Research* 41.1 (2004): 116–131.

Toubia, Olivier, et al. "Fast polyhedral adaptive conjoint estimation." *Marketing Science* 22.3 (2003): 273–303.

Toubia, Olivier, et al. "Measuring consumer preferences using conjoint poker." *Marketing Science* 31.1 (2012): 138–156.

Trope, Yaacov and Nira Liberman. "Construal-level theory of psychological distance." *Psychological review* 117.2 (2010): 440.

Tversky, Amos. "Elimination by aspects: A theory of choice." *Psychological Review* 79.4 (1972): 281.

Van der Lans, Ralf, Rik Pieters, and Michel Wedel. "Eye-movement analysis of search effectiveness." *Journal of the American Statistical Association* 103.482 (2008): 452–461.

Wakslak, Cheryl J., et al. "Seeing the forest when entry is unlikely: probability and the mental representation of events." *Journal of Experimental Psychology: General* 135.4 (2006): 641.

Wedel, Michel and Rik Pieters. "Eye fixations on advertisements and memory for brands: A model and findings." *Marketing science* 19.4 (2000): 297–312.

Wind, Jerry, et al. "Courtyard by Marriott: Designing a hotel facility with consumer-based marketing models." *Interfaces* 19.1 (1989): 25–47.

Yang, Liu, Olivier Toubia, and Martijn G. De Jong. "A Bounded Rationality Model of Information Search and Choice in Preference Measurement." *Journal of Marketing Research* 52.2 (2015): 166–183.

Yang, Liu, Olivier Toubia, and Martijn G. De Jong. "Attention, Information Processing and Choice in Incentive-Aligned Choice Experiments." Working paper. Columbia Business School (2017).

Yee, Michael, Ely Dahan, John R. Hauser, and James Orlin. "Greedoid-based noncompensatory inference." *Marketing Science* 26.4 (2007): 532–549.